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14. ABSTRACT
The attached is a compilation of presentations from the Workshop on Mobility and Control in Challenging Environments, which was held on Oct 5-6, 2006, at Olin College in Needham, MA.

Since written paper submissions were not required for the workshop, these presentations comprise the workshop proceedings.

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Report Title

Proceedings of the Workshop on Mobility and Control in Challenging Environments

ABSTRACT

The attached is a compilation of presentations from the Workshop on Mobility and Control in Challenging Environments, which was held on Oct 5-6, 2006, at Olin College in Needham, MA.

Since written paper submissions were not required for the workshop, these presentations comprise the workshop proceedings.

PROCEEDINGS OF THE ARO WORKSHOP ON MOBILITY AND CONTROL IN CHALLENGING ENVIRONMENTS

ARO Award Number: W911NF-06-1-374

Workshop Proceedings

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ARO Workshop on Mobility and Control in Challenging Environments

Olin College, Needham, MA
October 5 & 6, 2006

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8:50 – 9:05	Workshop Logistics and Welcome to Olin	Barrett
9:05 – 9:20	Workshop Sponsor Comments	Overholt
9:20 – 9:45	Design I Speaker 1	Wilcox
9:45 – 10:10	Design I Speaker 2	Borenstein
10:10 – 10:35	Design I Speaker 3	Playter
10:35 – 10:50	Coffee Break	
10:50 – 11:15	Controls Speaker 1	Kelly
11:15 – 11:40	Controls Speaker 2	Tsiotras
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12:05 – 12:30	Controls Speaker 4	Urmson
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3:30 – 3:45	Coffee Break	
3:45 – 4:45	Moderated discussion: Challenges in mobility and controls	Pratt
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7:00	Dinner	

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8:55 – 9:20	Exotic Environments Speaker 2	Rentschler
9:20 – 9:45	Exotic Environments Speaker 3	How
9:45 – 10:05	Exotic Environments Speaker 4	Frazzoli
10:05 – 10:20	Coffee Break	
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10:45 – 11:05	Motion Planning I Speaker 2	Spenko
11:05 – 11:20	Motion Planning I Speaker 3	Collins
11:20 – 11:45	Motion Planning I Speaker 4	Kobilarov
11:45 – 12:30	Moderated discussion: Perspectives on mobility and control in challenging environments	Pratt
12:30 – 12:40	Wrap Up	Iagnemma
12:40 – 1:30	Lunch and Adjourn	

Saturday, October 7

Visit to Team O'Neil in New Hampshire for hands-on limit handling demonstrations and discussions

12:00	Meet at Littleton Hampton Inn, caravan to Team ONeil
12:30 –1:30	Discussion of driver cues and vehicle dynamics
1:30 – 3:30	Hot laps in race prepared Ford Escape, SOF/In-theater maneuver demonstrations
3:30 – 4:30	Post-demonstration Q&A and facilities tour

Franklin W. Olin College of Engineering

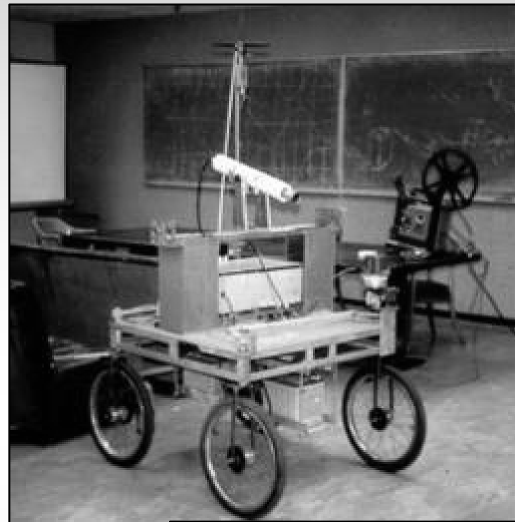
Workshop on Mobility and Control in Challenging Environments

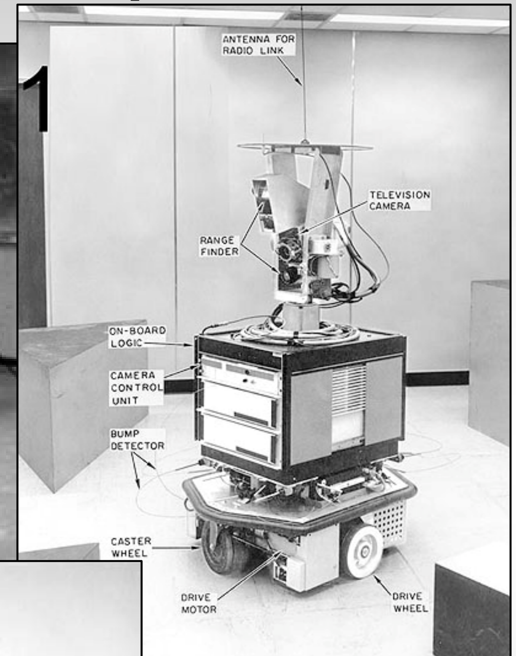
Olin College, Needham, MA

October 5 & 6, 2006

Mobile Robots—Historical Perspective

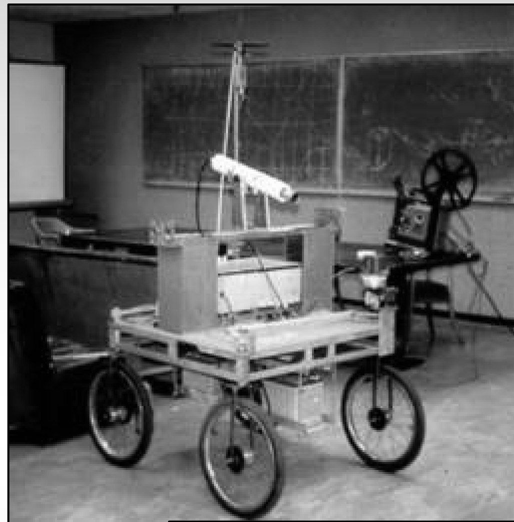
- Early mobile robots
  - SRI Shakey, 1969
  - Stanford CART, 1970
- Classical application
  - Research labs
  - Hospitals
  - Warehouses
  - Factory floors
- Operation at low speeds in structured, benign environments
  - Mobility usually not a focus

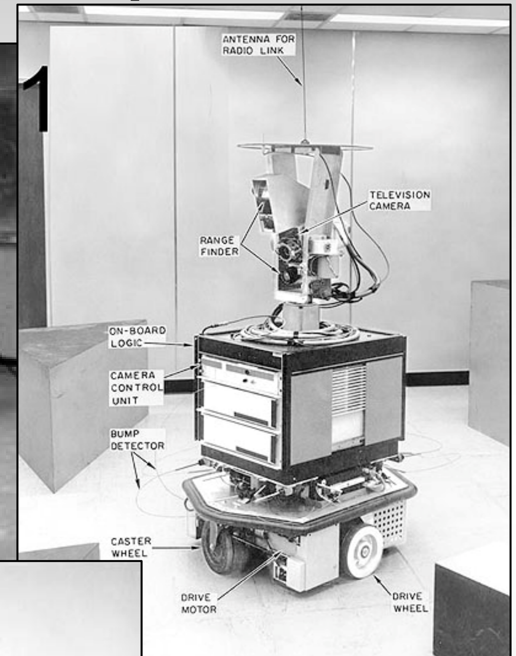




Mobile Robots—Historical Perspective

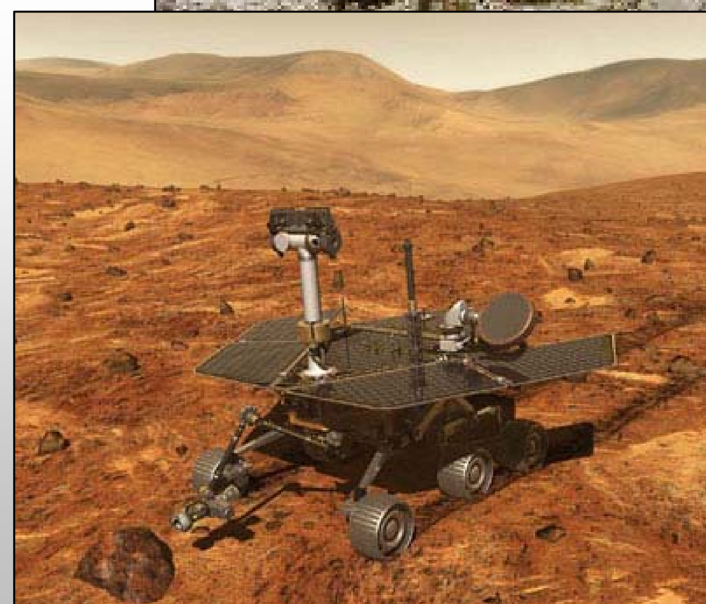
- Properties of (many) early mobile robots
  - “Pizza box on wheels”
    - Little consideration of suspension and drive system
  - Operation in static, planar environment
    - Simple environment interaction models
    - Binary obstacle/free space representation
  - Kinematic control





Mobile Robots—“Next Generation” Applications

- Civilian applications
  - Hazardous/disaster site inspection
    - WTC, Chernobyl, Katrina
  - Planetary exploration
    - Sojourner, MER, MSL
  - Passenger vehicles
  - Surgery and medicine
  - Industrial applications
    - Underground mine operations, forestry, undersea surveying

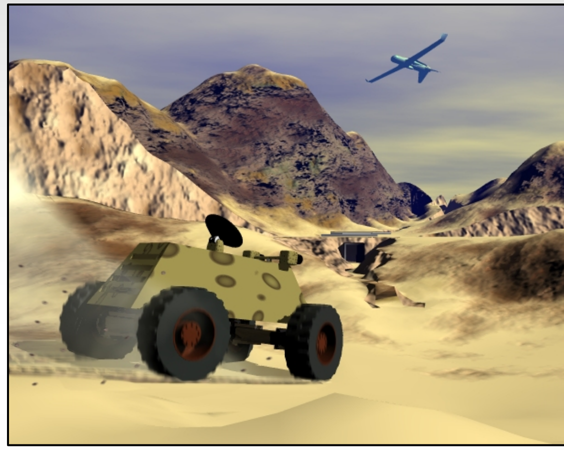


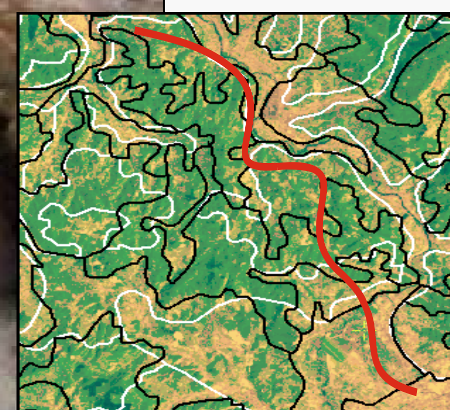
Mobile Robots—
"Next Generation" Applications

- Military application
  - Scout/inspection in dangerous areas
  - Inspection/disposal of suspicious objects (IED)
  - Battlefield rescue
  - Surveillance and reconnaissance
  - Material transport

Mobile Robots— “Next Generation” Applications

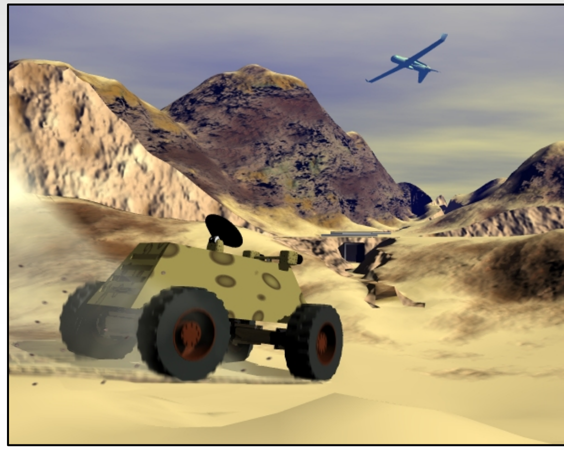
- Operation at high speeds in unstructured, hazardous environments
  - Mobility is critical
- Requirements of next-generation mobile robots
  - Design for high mobility
    - Innovative suspension/drive system
    - Design for invertability, modularity

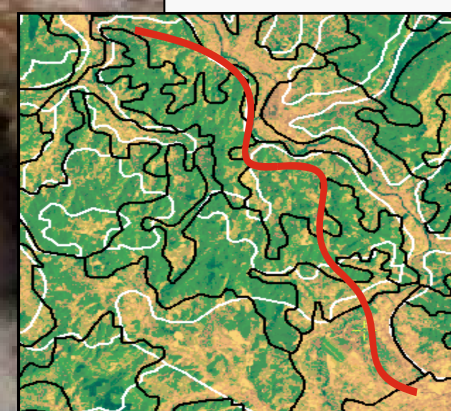




Mobile Robots—
“Next Generation” Applications

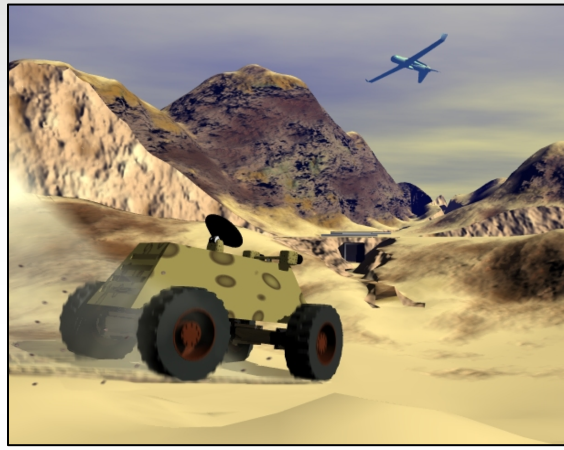
- Operation in dynamic, 3D environment
  - Sophisticated understanding of environment interaction
    - Via modeling, sensing, or design
    - Non-binary obstacle/free space representation
    - Geometric and non-geometric hazards

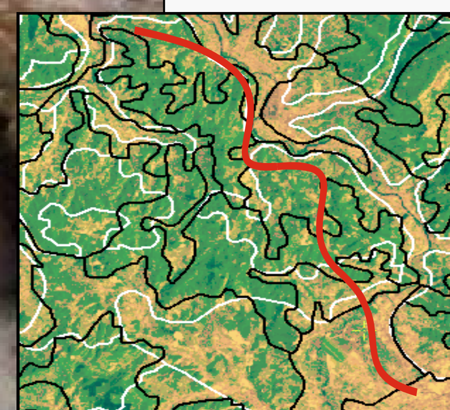




Mobile Robots—
"Next Generation" Applications

- Control at robot performance limits
  - Consideration of robot dynamics
  - Consideration of uncertainty
  - Effect of robot-environment interaction



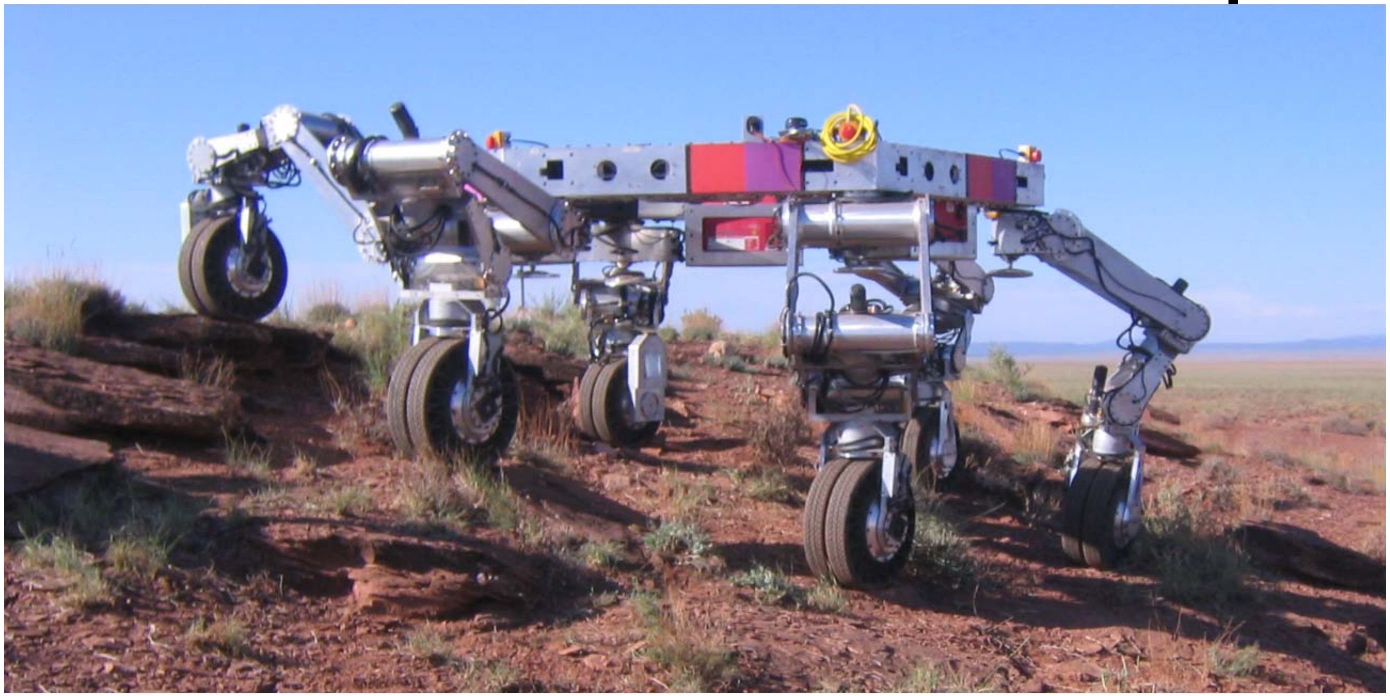
Workshop Purpose

- Workshop purpose: Survey state-of-the-art in design, control, and motion planning of mobile robots operating in extremely challenging environments
  – Outdoor mobile robots on Earth, but also…
    - Planetary surface systems
    - Underwater robots
    - Aerial robots
    - Surgical systems
- Identify fundamental research challenges across problem domains
- Identifying innovative potential solution paths

ATHLETE: An All-Terrain Adaptive Suspension Vehicle

Brian Wilcox
Autonomous Systems Architecture and Program Development Office
Jet Propulsion Laboratory
5 Oct 2006

ATHLETE: the All-Terrain, Hex-Limbed Extra-Terrestrial Explorer



- **Two functional prototype vehicles were built in 2005 as part of NASA “Technology Maturation Program”**
- **Each vehicle is ~850 kg, hexagonal frame 2.75 m across, ~300 kg max payload, top speed of ~10 km/h (2.8 m/s), power budget ~5000W, max limb tip speed at full extension of about 0.2 m/s**

Drive off the dunes – not sped up (~8 km/h)

Where we are, Where we want to be...

- Today we can:
  - roll 10 cm, stop to equalize weight on each wheel, repeat N times
  - adjust body centering and pose every N force redistribution cycles
- Work in progress:
  - continuous weight redistribution and body reposing
  - detect anomalous forces on a wheel, autonomously make decision to put some or all of its weight on other wheels, and lift and advance selected wheel in a lightly-loaded “terrain following” mode
  - fully autonomous walking on extreme terrain
  - rappelling on steep slopes

ATHLETE: Current Capabilities

- Show Movie

Lessons Learned, and Lessons we expect to Learn

- Redistributing weight on all wheels is incredibly important
  - imperceptible pose changes every 10 cm is “all the difference” in traversing even moderate terrain
- Deciding when a wheel should be “relieved of its responsibility” to carry its share of weight may be as simple as keeping the horizontal force on each wheel zero
  - at constant speed all wheels should have purely vertical net force
  - if negative horizontal force component appears on a wheel, reduce weight on that wheel until horizontal component disappears (at the expense of higher rolling resistance on all other wheels).

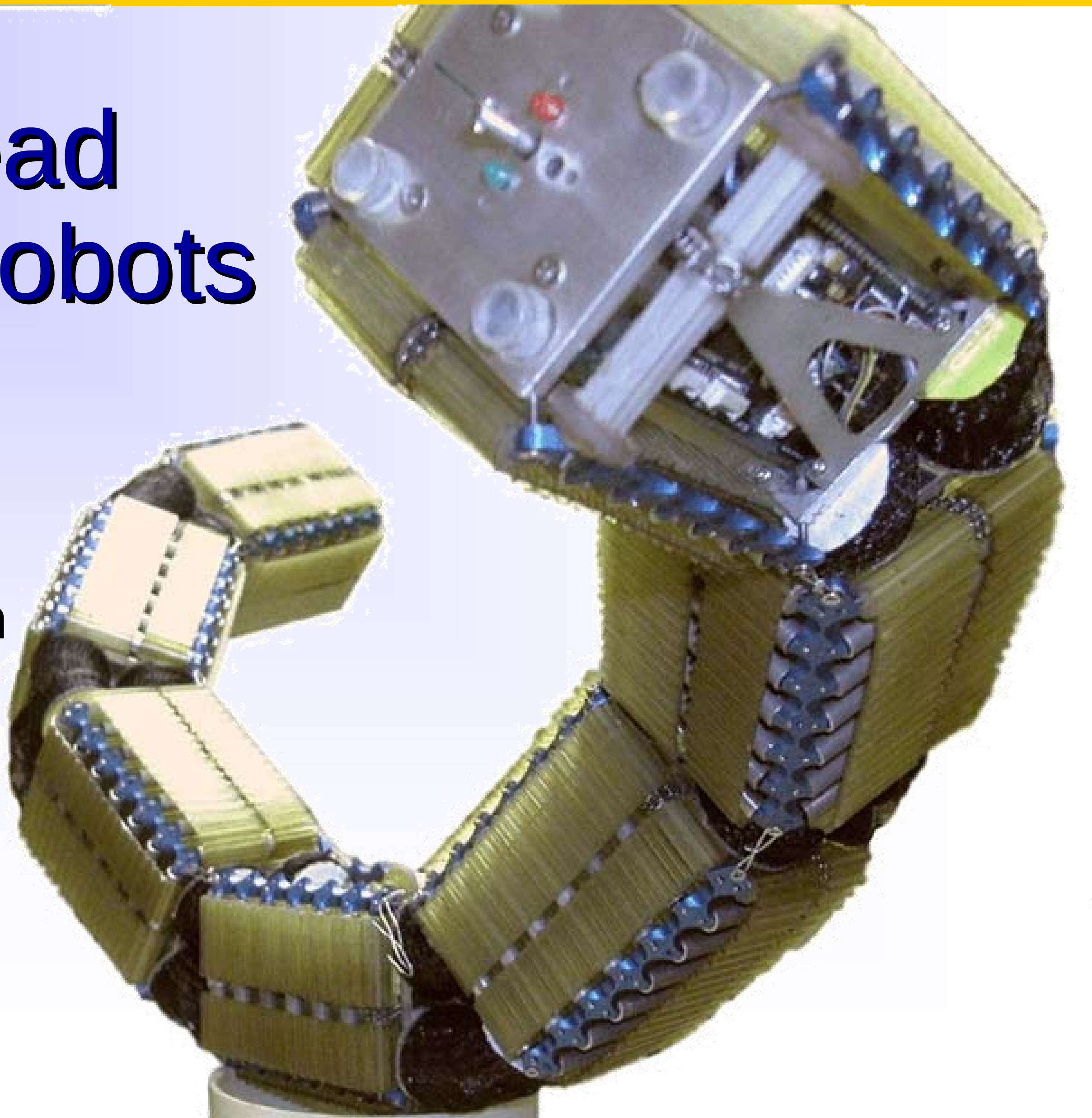
Summary and Conclusions

- ATHLETE provides a rich environment in which to study the adaptive-suspension problem.
- Simple force-redistribution and body reposing algorithms are very effective.
- Six (or more) smaller wheels and motors on limbs can have less mass (and cost) than three or four larger wheels and motors without limbs, since the “walk out” contingency option means they don’t need to satisfy all the worst-case requirements.

University of Michigan

ARO Workshop on Mobility

The OmniTread Serpentine Robots



Presenter:

Johann Borenstein

Research Professor

University of Michigan

Versatility

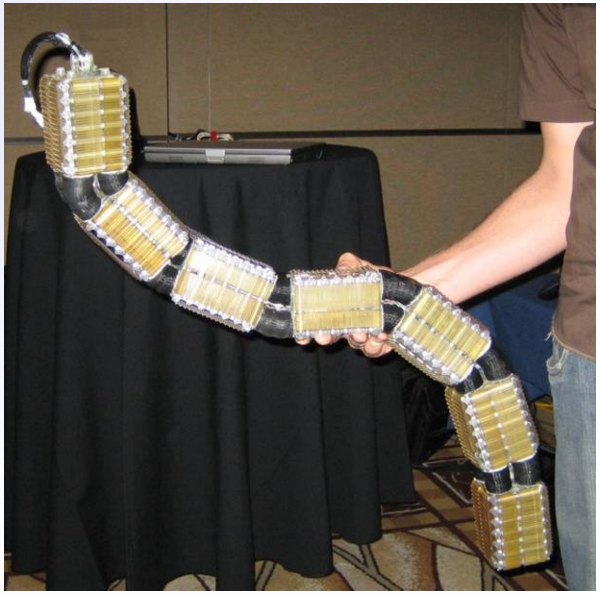
We have developed and built two OmniTread Models:

Model OT-8

Can pass through an 8-inch diameter opening

Model OT-4

Can pass through a 4-inch diameter opening

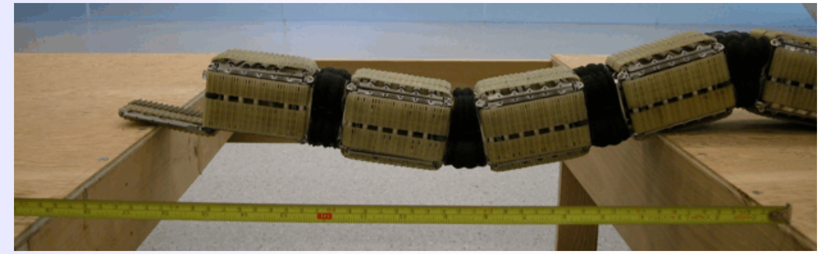


Capabilities: OT-8

- Can travel over rocks & rubble
- Can travel over deep sand
- Can travel through dense underbrush
- Can traverse high vertical obstacles
- Can traverse wide gaps

Capabilities: OT-4

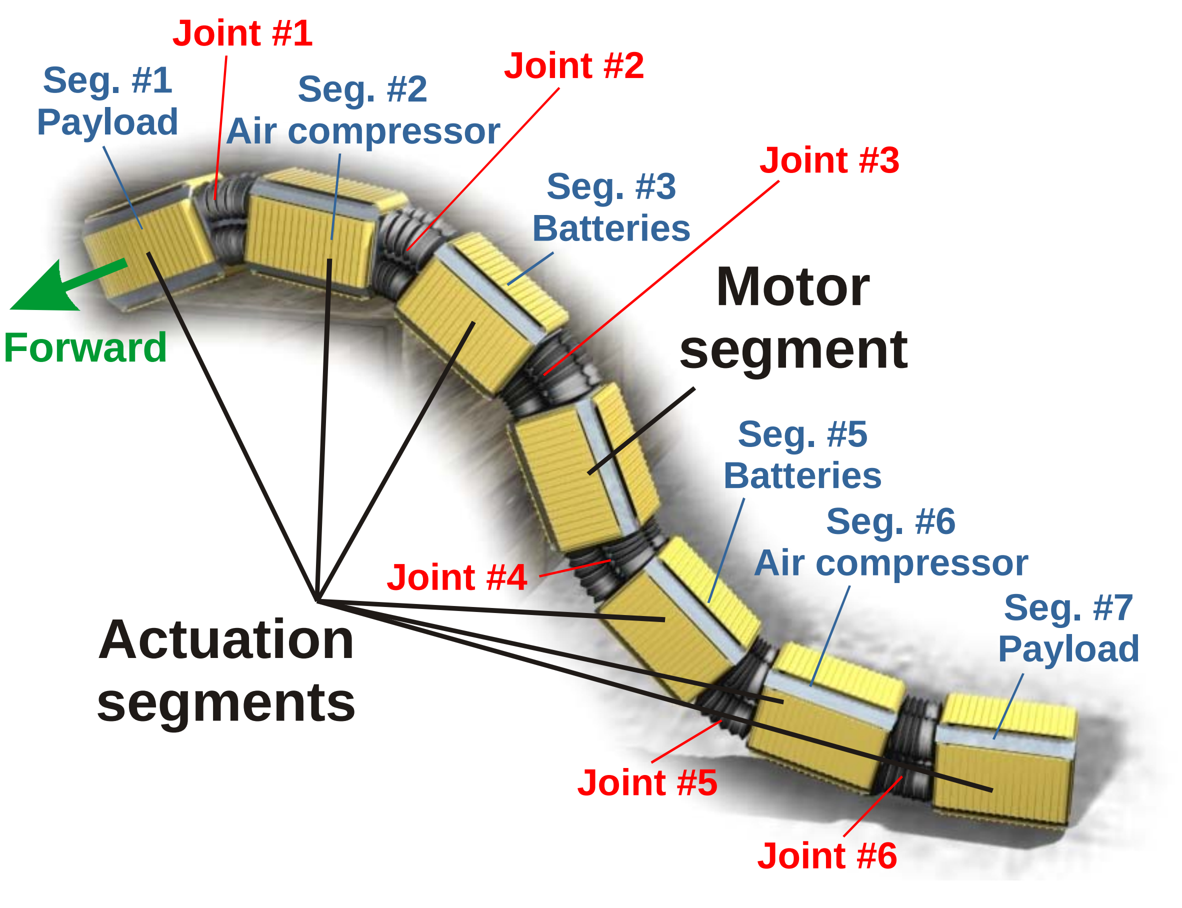
- Can travel over rocks, gravel, rubble
- Can traverse high vertical obstacles
- Can traverse wide gaps
- Can travel inside pipes
- Is completely untethered
    - Batteries last for up to 75 minutes of drive time on easy terrain



The remainder of this talk focuses on the OT-4

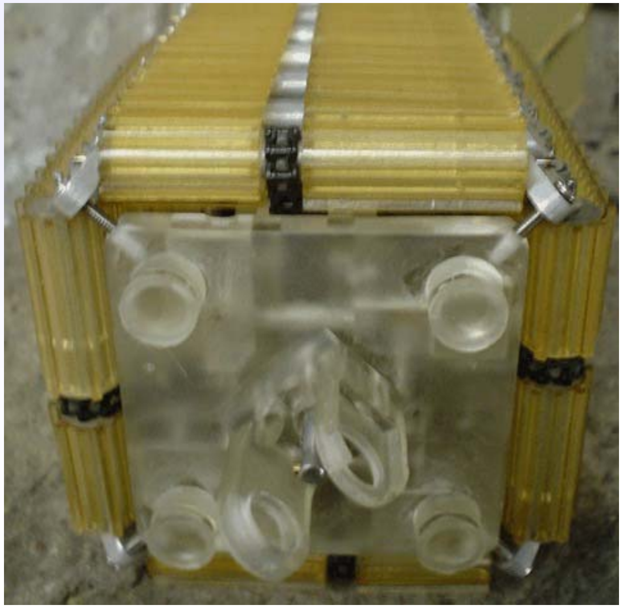
Specifications and Nomenclature

Parameter	Specification
Structure:	7 segments 6 joints
Drive System:	Tracks on all sides. Electric motor in center segment drives all tracks
Dimensions: Length = Height = Width = Weight =	 94.0 cm (37") 8.5 cm (3.35") 8.5 cm (3.35") 4.0 kg (8.8 lbs)
Joints:	Pneumatic bellows powered by two onboard micro-compressors



Design Features: Maximum Coverage by Tracks

- Contact between environment and OT-4's non-propelling surface impedes motion.
- Conversely, contact between the environment and a propulsion surface produces motion.
- To increase propulsion we cover *all sides* of the OmniTreads with extra-wide tracks.
- Additional advantages of tracks-all-around:
  - Massive redundancy in case of track failure
  - OT-4 is indifferent to rolling over
    - Roll-overs are inevitable when the slender bodies of serpentine robots travel over rugged terrain
- Disadvantage: High power consumption
- Remedy in OT-4: Track clutches.
  - 28 micro-clutches allow operator to engage and disengage every track pair individually.



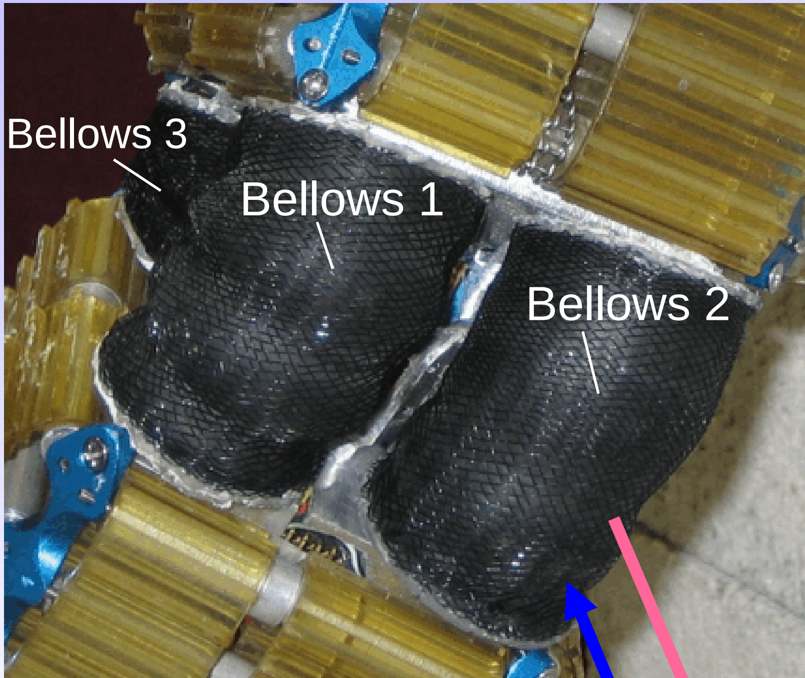
Design Features: Pneumatic Joint Actuation

- **Pneumatic joint actuation provides natural and easily controllable compliance**
  - **Natural compliance is of critical importance, since propulsion depends on optimal traction between propelling surfaces and arbitrarily shaped terrain features.**
  - **Maximal traction is achieved by letting joints go limp, allowing robot to conform compliantly to the terrain.**
- **Joint stiffness can be controlled in real-time to any level from completely compliant to completely stiff.**

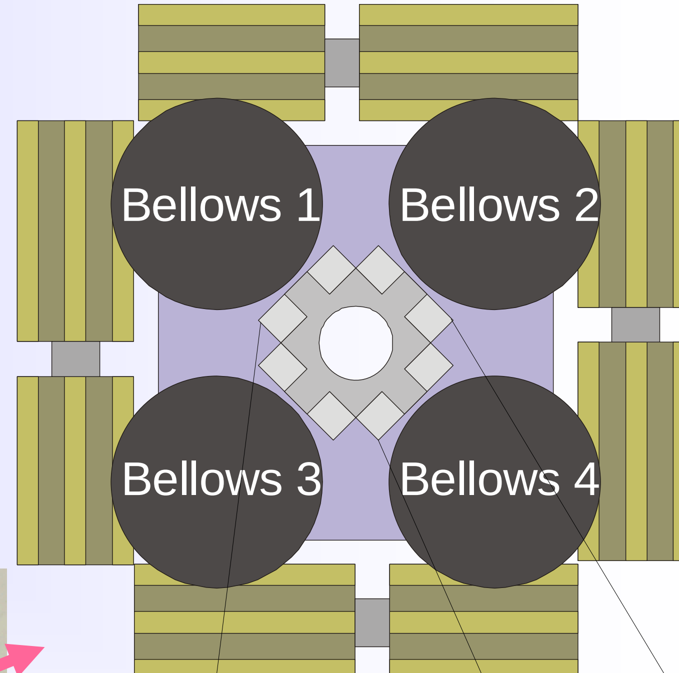
OmniTreads achieve maximal traction and propulsion by *complying naturally* to rough terrain.

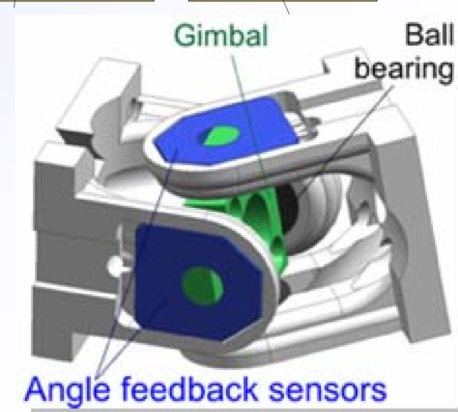
Control of the Pneumatic Joints

Close-up of one of six OT-4 joints

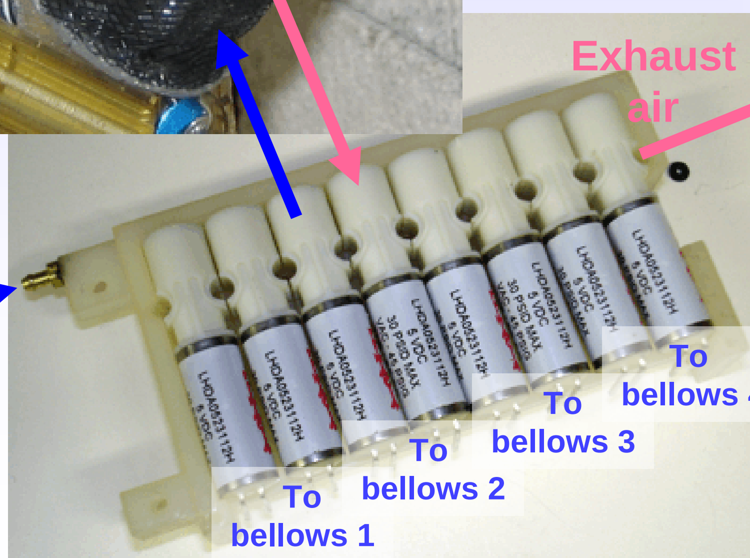


Cross-section of the OT-4 joint





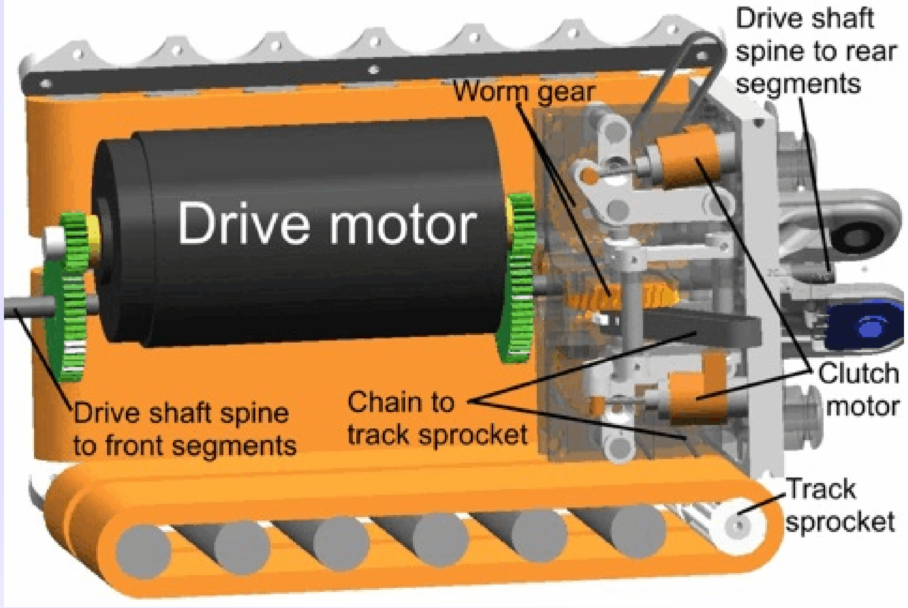
Compressed air supply inlet

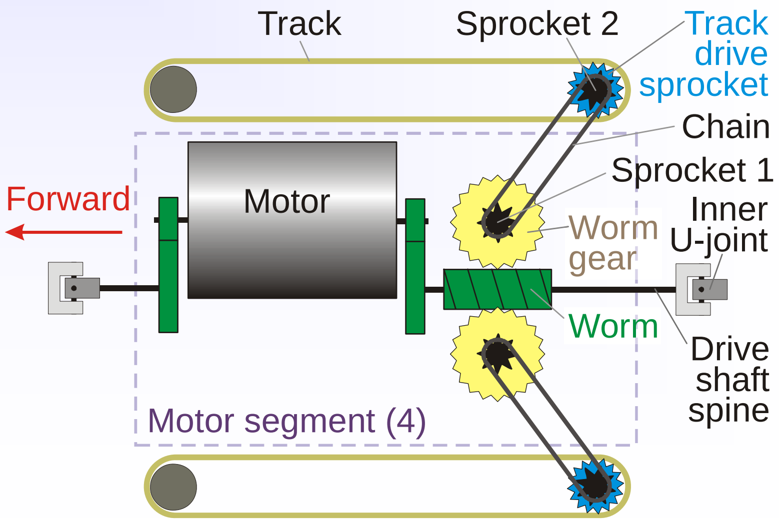


An array of 8 on-off valves controls one OT- 4 joint

Design Features: Drive Shaft Spine and Clutches

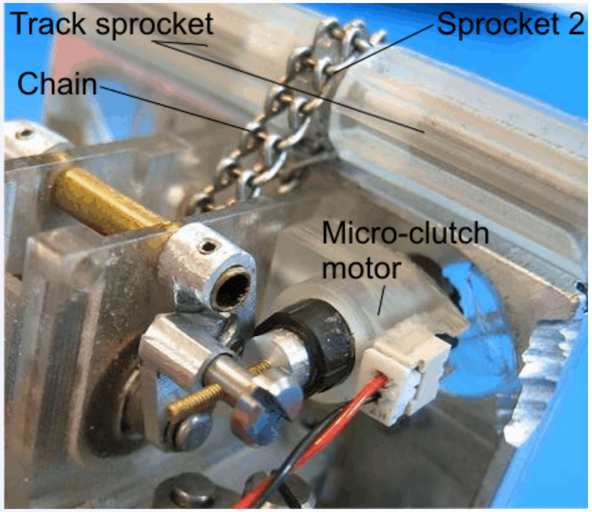
- **Single motor located in center segment drives articulated *drive shaft spine* that runs through all segments.**
  - **Optimizes weight distribution (center heavy, ends lights)**
  - **Saves weight, volume, and power**
  - **But limits range of motion of joints**
- **In each segment, worm on drive shaft spine drives four worm gears, which transfer power to the four track pairs of the segment via chains.**
  - **Each worm gear can be disengaged from the worm by a micro-clutch.**



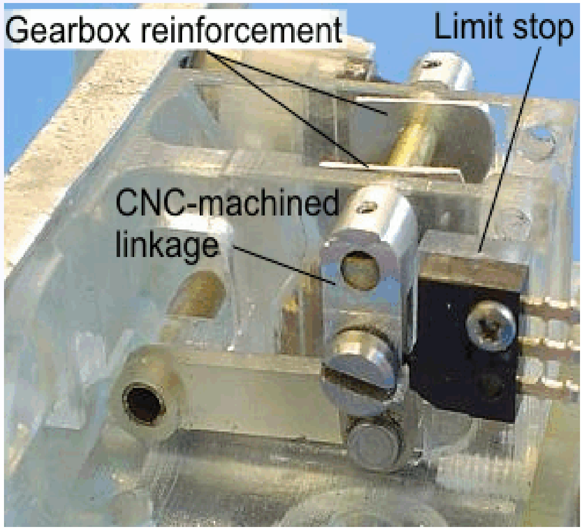


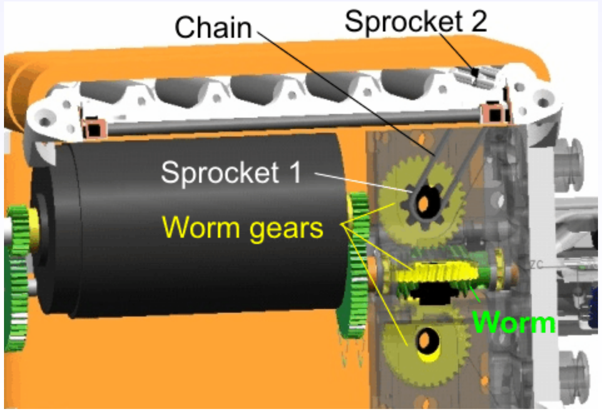
Micro-clutches

- The OT-4 has 28 micro-clutches, one for each side of each segment
  - Micro-clutches disengage the bronze worm gear by lifting off the worm.
- Main advantages:
  - Reduce electric power consumption by disengaging tracks that are not in use
  - Reduce overall torque on the drive system when disengaged
  - Can disengaged damaged branches (there are 28) of the drive train
- Main disadvantage:
  - Add significant complexity to hardware and software
  - Add some weight



Top: left side of clutch. Bottom: right side

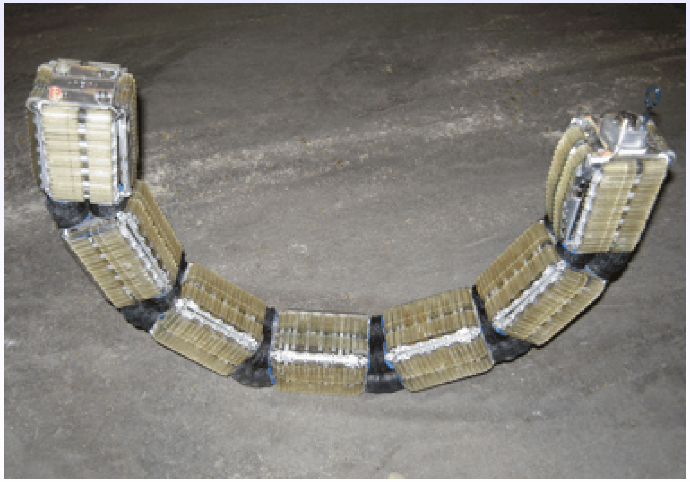




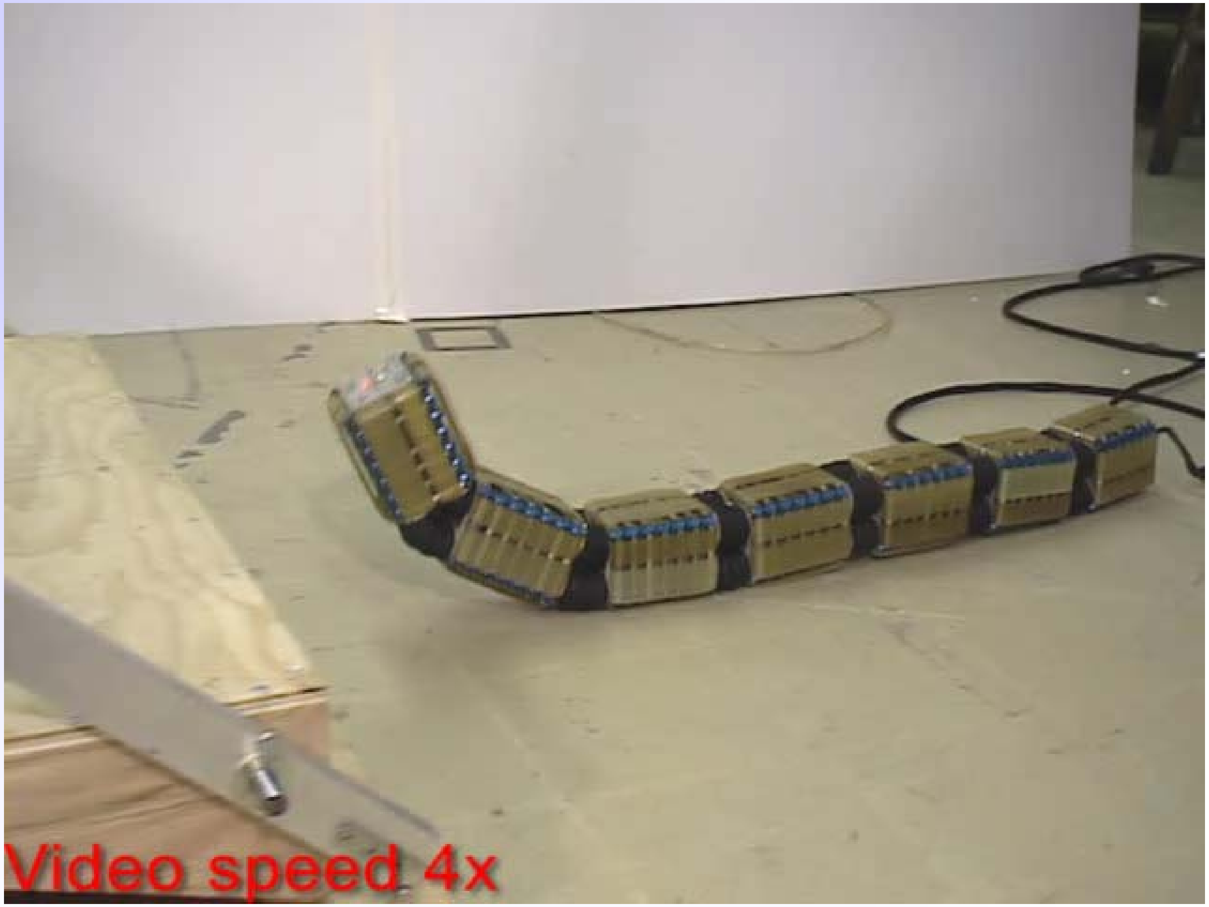
Motor segment, showing motor & drive train

Performance Specifications

Parameter	Performance
Control & Energy:	Completely tetherless
Onboard energy:	Sufficient for 75 min. continuous driving on smooth terrain
Speed:	15 cm/sec
Can climb vertically in pipes:	4, 6, and 8 inch diameter
Can scale vertical walls:	Up to 40 cm (16”) high
Can bridge gaps:	Up to 50 cm (19”) (more than half its own length)

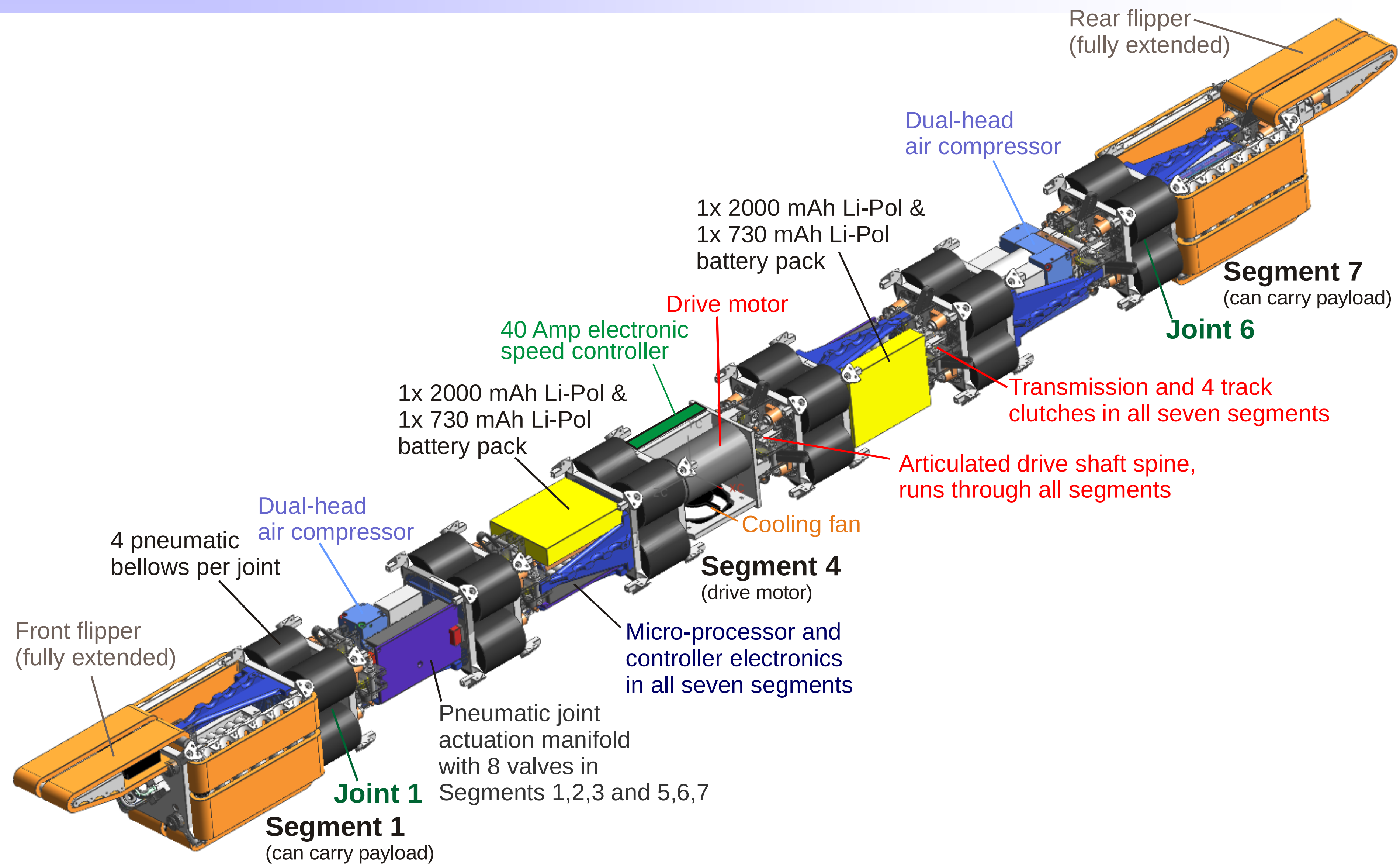


OT-4 flexing its muscle.
Here: Lifting up three distal segments

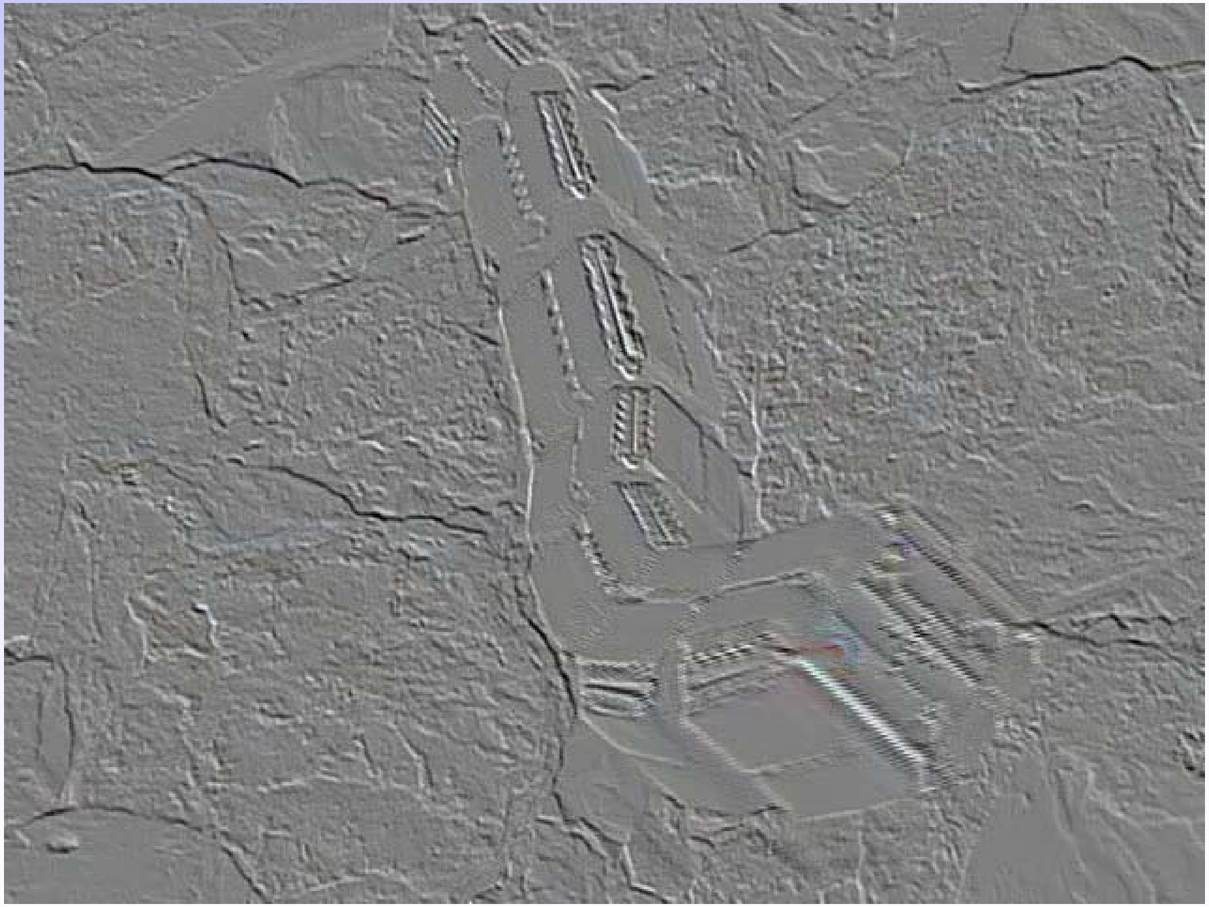


Steep stair climb - motion sequence based on “7G”

Technical Summary



The OT-4 in Action – Video Clips



Intelligent Control with 7G

- **Problem with serpentine robots: How to control many degrees-of-freedom.**
  - **Currently three operators are needed to control the 13 DOF of the OT-4.**
- **Solution: AI Researchers Bill Hutchison and Betsy Constantine are developing the "7G" self learning software that helps the OT-4 cope with difficult terrain.**

Future Work

- Improve and harden mechanical system
- Develop semi-autonomous control
  - Currently: 3 operators needed
    - That is unacceptable
  - One operator is our goal
  - Computer-assisted control requires sophisticated sensors
    - And sophisticated self-learning software, e.g., 7G
- Integration, commercialization

So then, when it's all done…

- **As always, the visionaries in Hollywood may know the answer long before we scientists have a clue.**


This presentation is done

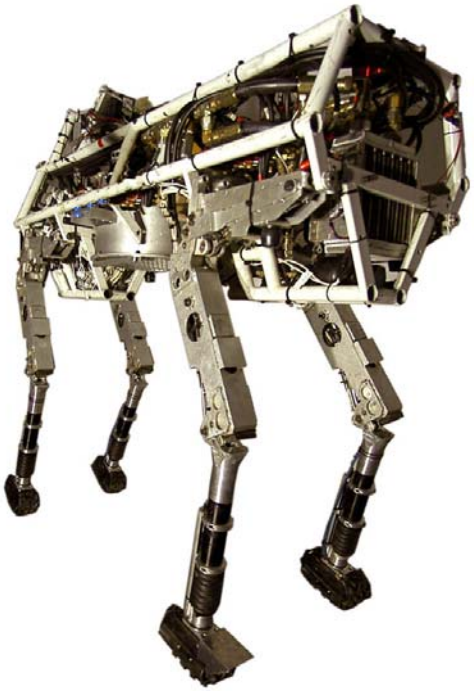
Dynamic Robots at Boston Dynamics

Robert Playter

Vice President

515 Massachusetts Ave
Cambridge MA 02139
www.BostonDynamics.com

Robotics at Boston Dynamics



BigDog – Dynamic quadruped

LittleDog – Learning Robot

Legged Robot Mule

RiSE – Climbing robot

RHex – Packable rough-terrain

MDMR – Snake

NAV – Nano-Air Vehicle

QRIO – Sony Dream Robot


RHex
DARPA

Rhex

BostonDynamics

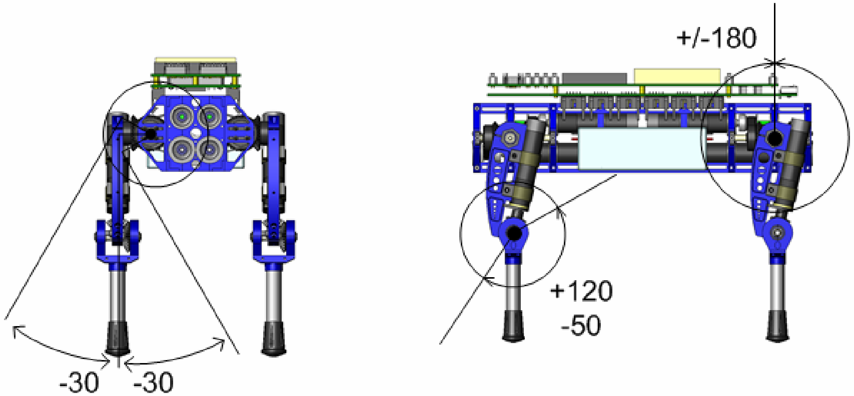
RHex Devours Rough Terrain

LittleDog Learning Robot

- *Common Platform for "Learning locomotion" DARPA program*

3 kg, 12 actuators

- *Joint angle sensors*
- *Foot contact sensors*
- *Inertial measurement unit*
- *Wireless*



LittleDog Learning Robot

IPTO PM Larry Jackel,

Clip from Government Testing

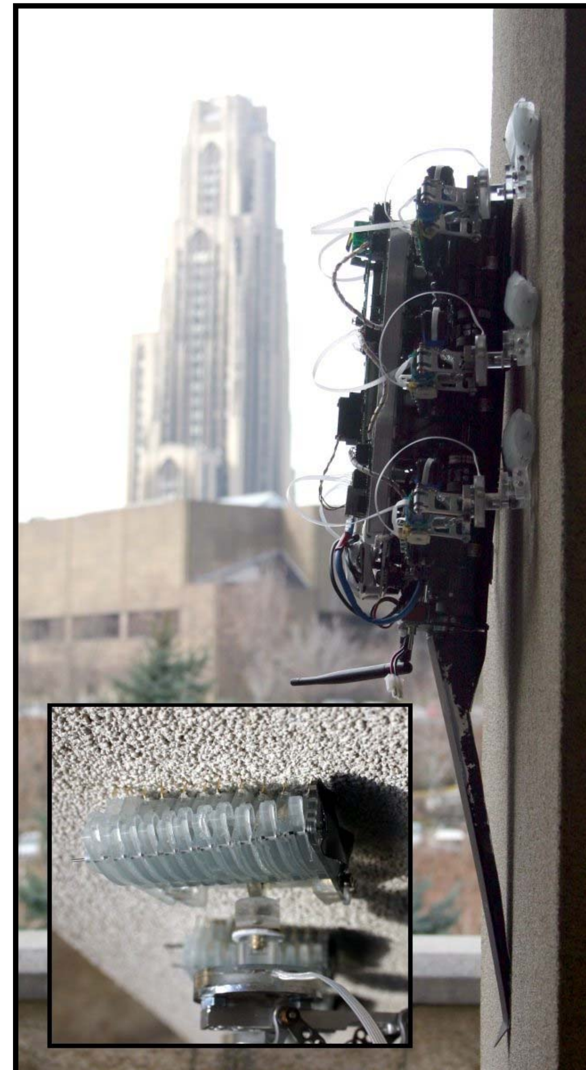
Performers:

- CMU
- MIT
- IHMC
- Stanford
- U Penn
- USC

Robotics in Scansorial Environments

BostonDynamics

K. Autumn	Lewis & Clark
M. Cutkosky	Stanford
R. Fearing	UC Berkeley
R. J. Full	UC Berkeley
D. E. Koditschek	U Pennsylvania
M. Buehler	Boston Dynamics
A. A. Rizzi	Boston Dynamics



RiSE

RiSE

BigDog Goal: Be the world's most capable dynamic legged robot, with exceptional rough-terrain mobility, autonomy and speed.


Go Where
Soldiers Go


Go Where
Soldiers Go

BigDog

BostonDynamics

Risks of Bio-inspired Design

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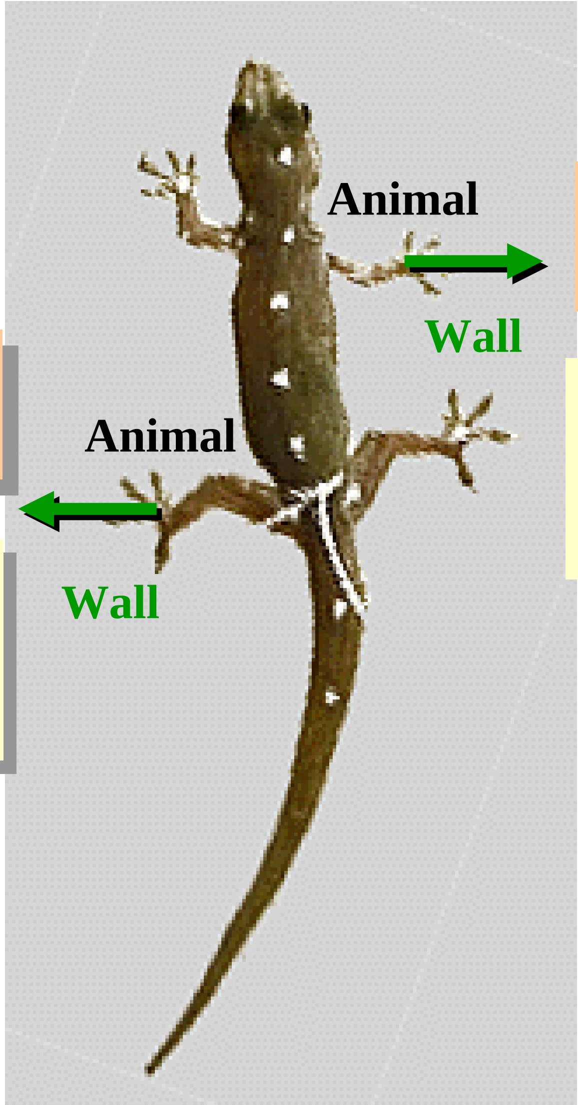
Common Themes

- Bio-inspired design
- Mechanical design ↔ Intrinsic mobility
- Active modulation of contact forces
- More complex terrains require more sensing and control

Lateral Wall Reaction Force



Animal

Pulls Toward Body

Wall

Pulls Away from Body

Animal

Pulls Toward Body

Wall

Pulls Away from Body

Versatile Foot Trajectory with only two leg motors:

Leg= rotating (1dof), compliant four-bar linkage (1dof)

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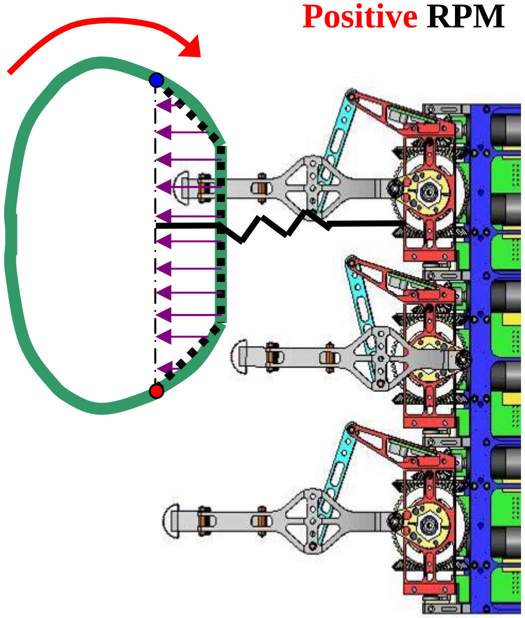
Wall Operation

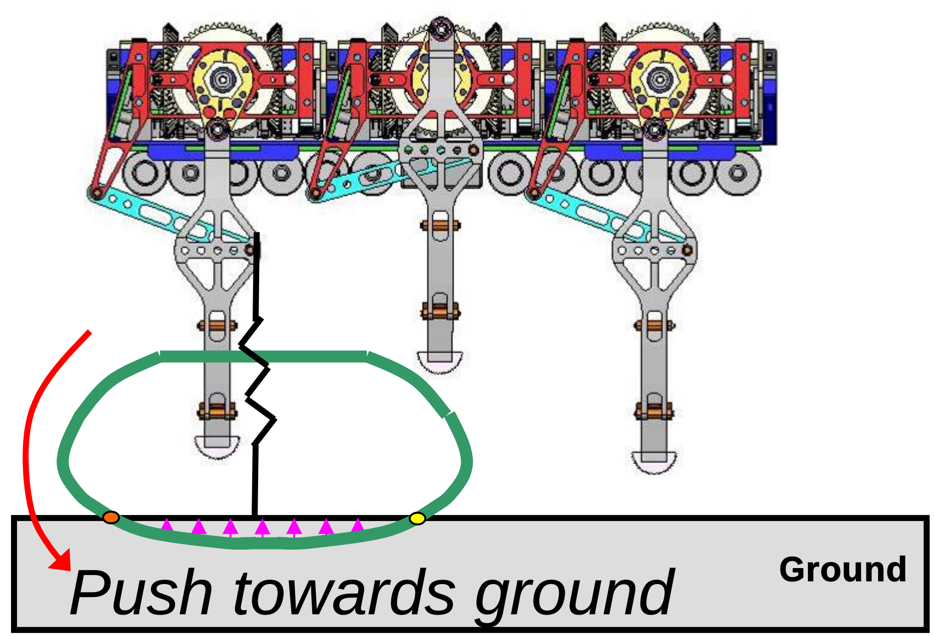
CRANK DIRECTION
Positive RPM



Pull towards body

Ground Operation

CRANK DIRECTION
Negative RPM



Legs

CONCORD FIELD STATION
HARVARD UNIVERSITY

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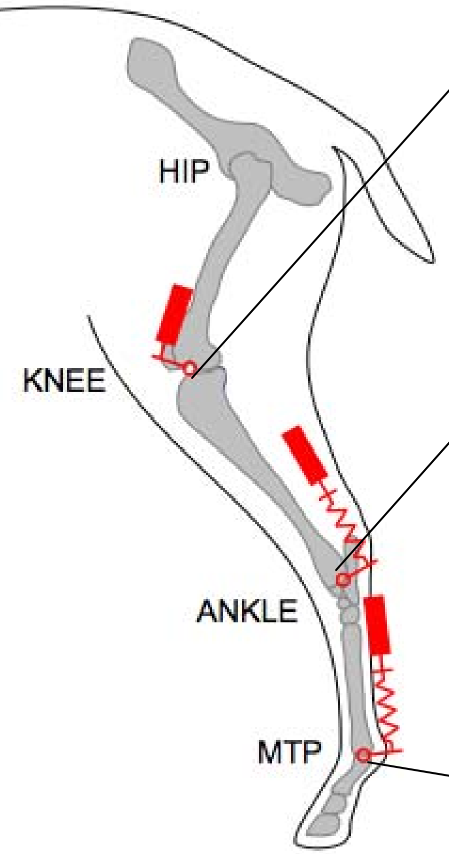
Animal — **BigDog**

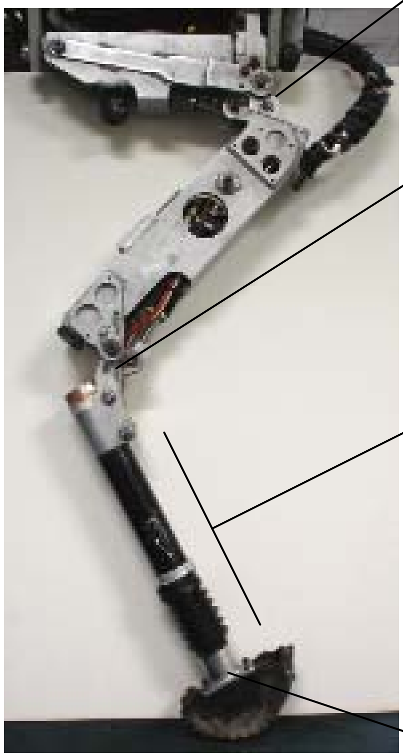


Actuation

Compliance
+
Actuation

Compliance
+
Dissipation

Less actuation
More compliance



Actuation

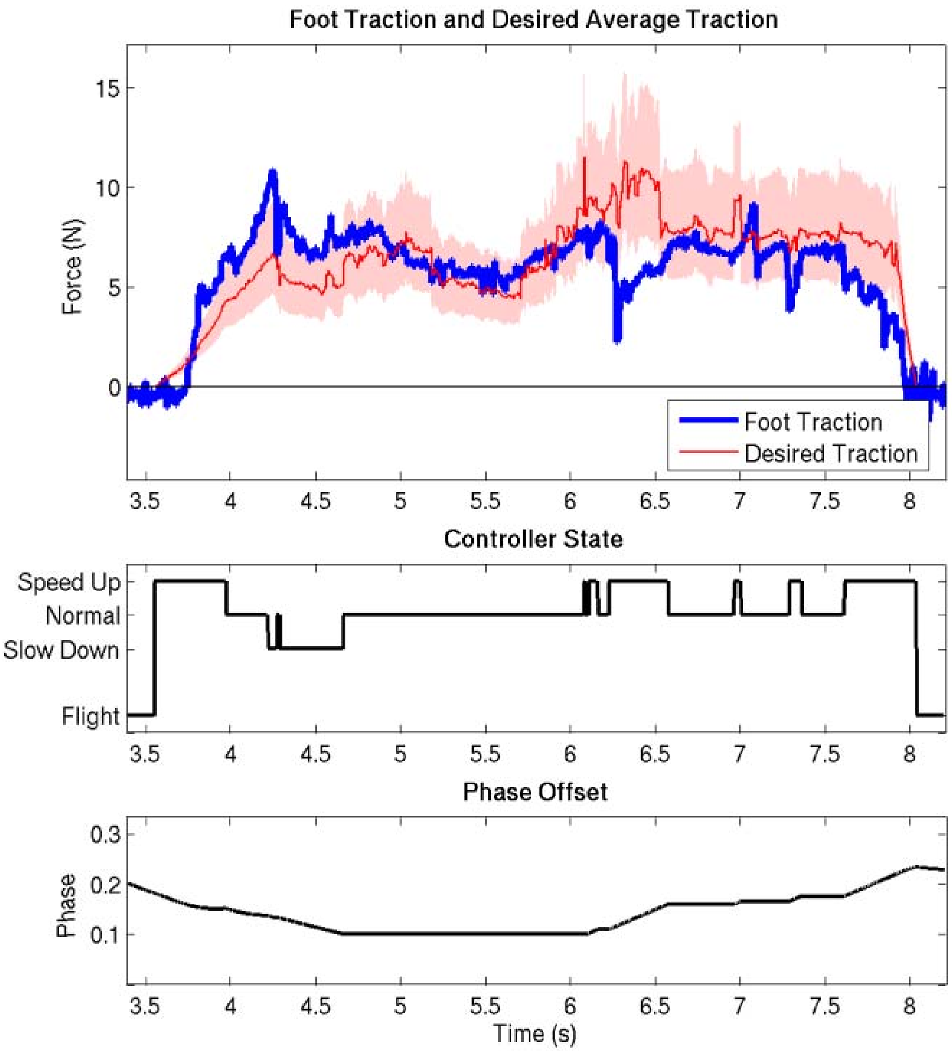
Compliance

Compliance
+
Dissipation

A. Biewener, D. Lee, Harvard Concord Field Station

Active Force Control

- Control traction for robust climbing
- Leg Speed adjusted based on sensor readings



Dynamic trot control

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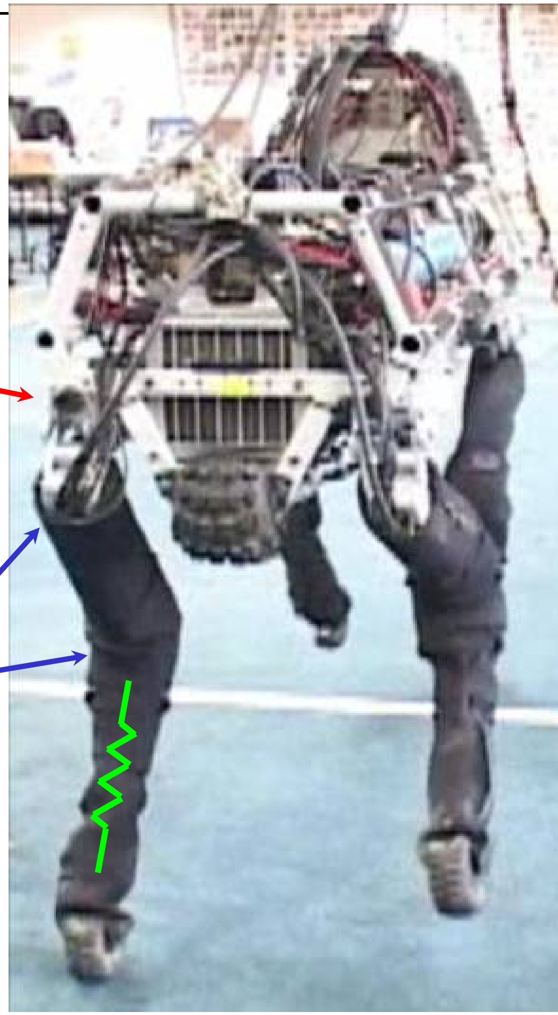
Torque control

Position control



Stance Leg

Stance Leg Control

Torque control hip ab/adduction keeps body roll at level

Position control flex/ extend joints to

- *sweep foot backwards*
- *adjust the compression of leg spring for body pitch and height control*

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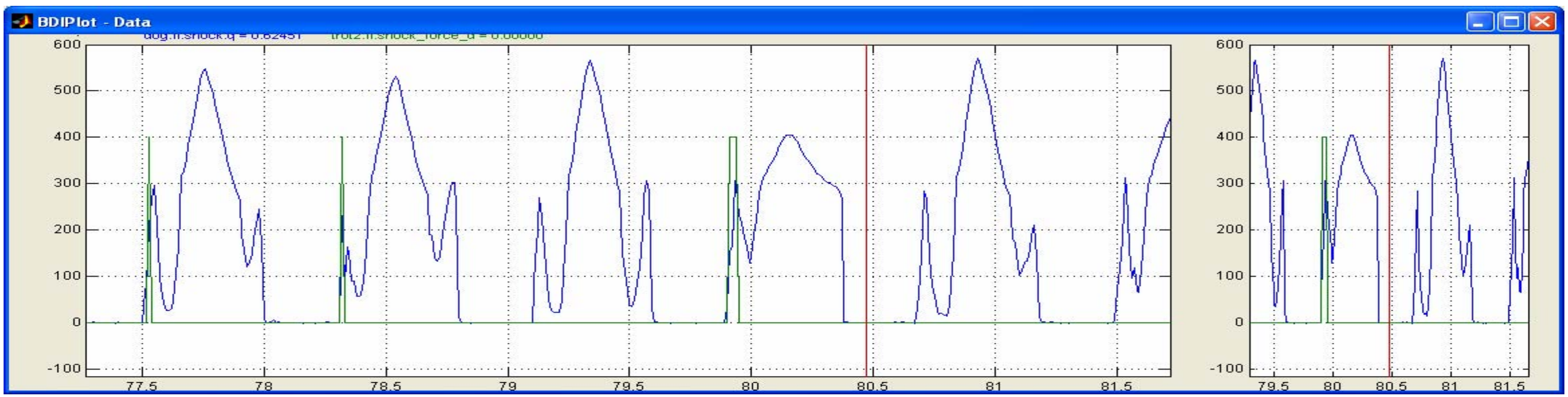
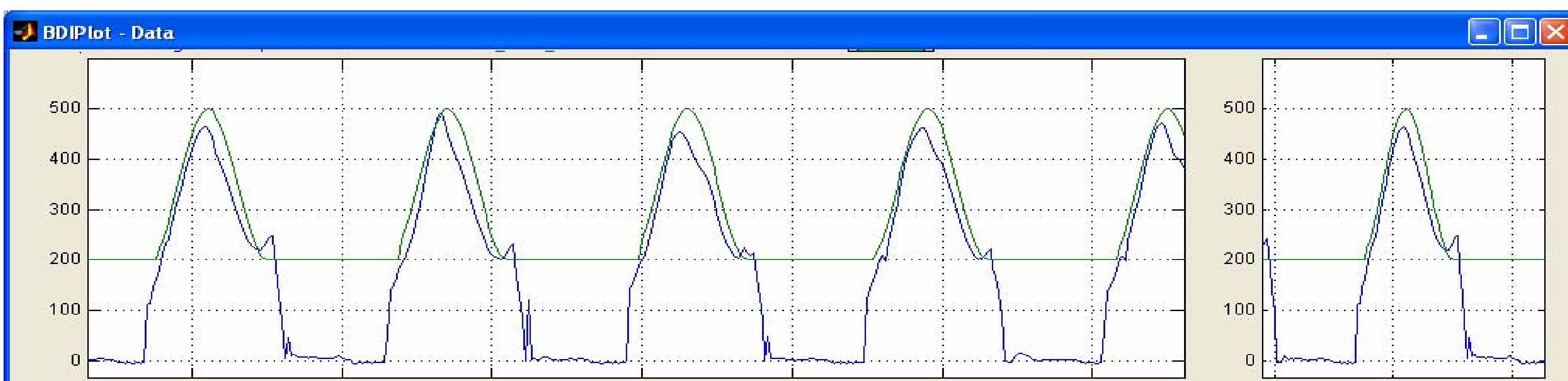
BigDog Active Force Control

Shock Loading Improvement:

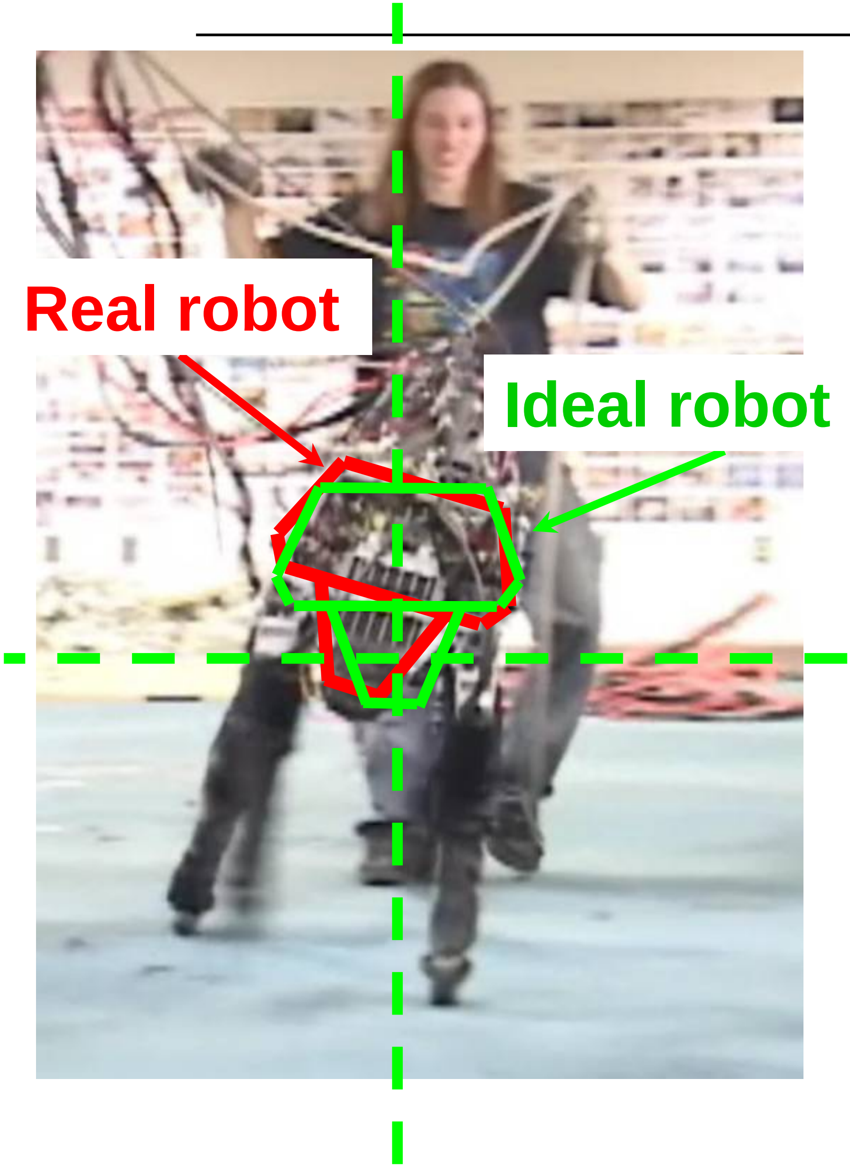
Before:



After shock pressure reduction and load control:



Dynamic trot control

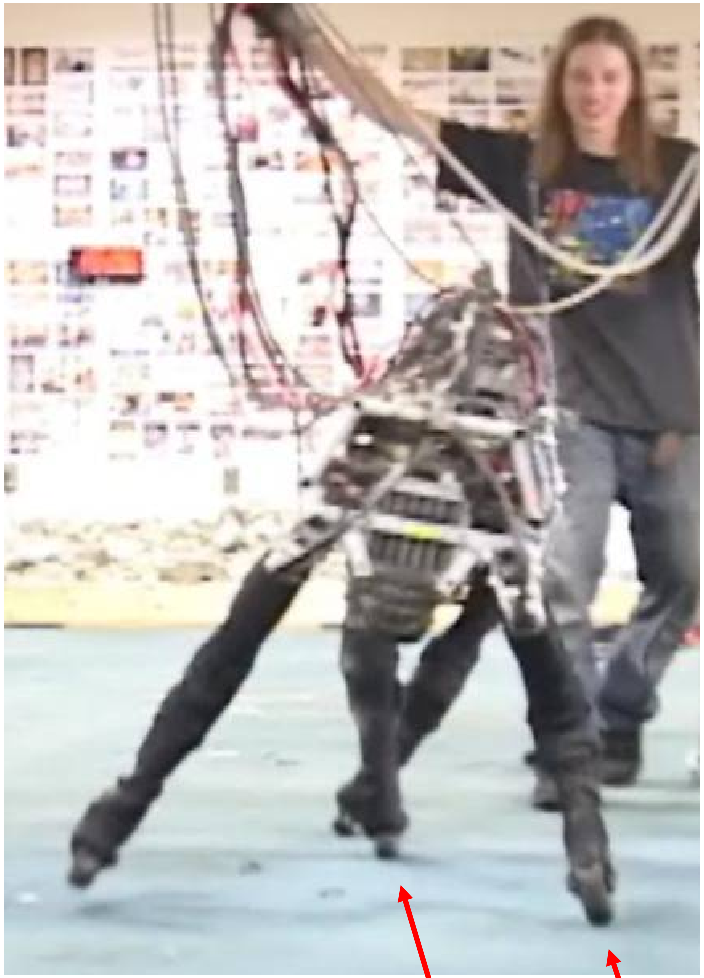


Swing Leg Control – Part 1:

Swing legs move with respect to an "ideal" robot that is straight and level

Dynamic trot control

BostonDynamics



Swing Leg Control – Part 2:

<u>Dynamic sideways balance</u>

Movement of stance legs affect placement of swing legs

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Increasing Terrain Challenges

Indiscriminate foot placement

- Steady state behavior
- Reactive control
- Low terrain sensing

Increasing Terrain Challenges

Indiscriminate foot placement

- Steady state behavior
- Reactive control
- Low terrain sensing

Intermittent foot placement

- Steady state behavior with transitions
- Recovery
- Odometry
- Medium terrain sensing

Step Obstacle

Jumping

- Running at 3.3 m/s (7.4 mph)
- Does not include engine weight (30lbs)

Jumping

Increasing Terrain Challenges

Indiscriminate foot placement

- Steady state behavior
- Reactive control
- Low terrain sensing

Intermittent foot placement

- Steady state behavior with transitions
- Recovery
- Odometry
- Medium terrain sensing

Precise foot placement

- Unsteady dynamics
- Predictive control
- Accurate odometry
- High Terrain sensing

The End

Deliberation and Exception in Challenging Environments

Alonzo Kelly
Carnegie Mellon
National Robotics Engineering Center

Outline

- Challenges of Challenging Terrain
- Stability Margin Estimation
- Trajectory Generation
  - Instrument Placement
  - Path Following
  - Cluttered Terrain Planning
  - Obstacle Avoidance

Challenges

Exception

- Difficulty level is high => autonomy will fail more often
- Risk level is high => results can be disastrous.

Fault tolerance, not algorithmic sophistication, will enhance robot survivability.

Deliberation

- (i.e. prediction and selection)
- Models must be 3D, perhaps volumetric
- Wheel-terrain interactions are central to motion prediction.
- Terramechanical properties are difficult to measure with noncontact perception sensing.

It takes more computation to produce a lower quality result.

Themes

- 1: Need fast, robust systems to detect and react to autonomy failure.
- 2: Adequate predictive models are both necessary and enabling.

Lack of a model is a predictable “disturbance”.

Stability Margin Estimation

A. Diaz-Calderon, A. Kelly "Online Stability Margin and Attitude Estimation for Dynamic Articulating Mobile Robots" IJRR, Oct/Nov 2005*.*

Motivation

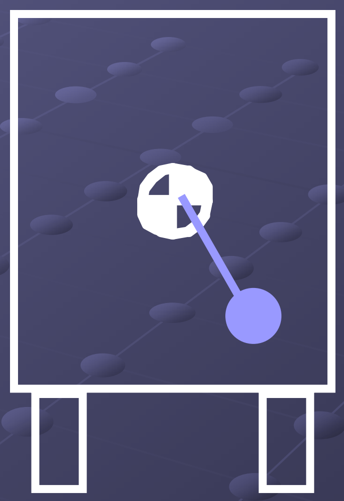
- Robot rollovers happen.
- Risk is increased
  - on slopes

    and/or
  - at high speeds
- Field robots must become competent despite these dangers.

These three robots rolled within 3 weeks of each other in 2003.

Approach

- Basic idea developed for legged robots long ago.
- Compute inertial properties (cg) in real time.
- Predict wheel liftoff rather than rollover.
  - Don’t need to know inertia.
- Measure specific force
  - Immune to drift.
  - Don’t need to know attitude.
  - Can actually measure it anyway.



Implementation

- IMUs, gyros, odometry, articulation sensing etc.
- Kalman Filter

gyro or speed/steer

$$\vec{t}_c = \vec{t}_\sigma + \vec{a}_c^{\,\sigma} + 2\vec{\omega}_\sigma \times \vec{v}_c^{\,\sigma} + \vec{\alpha}_\sigma \times \vec{r}_c^{\,\sigma} + \vec{\omega}_\sigma \times \vec{\omega}_\sigma \times \vec{r}_c^{\,c}$$

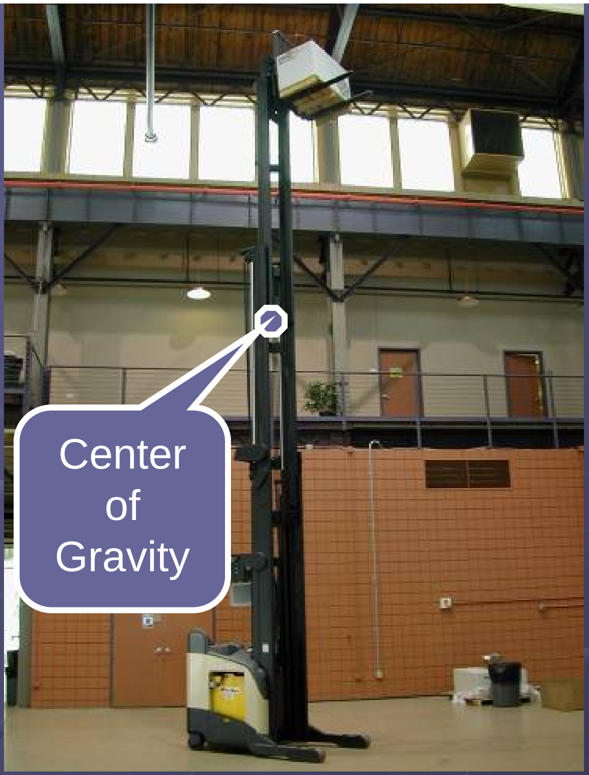
inclinometer numerical d/dt cg kinematics

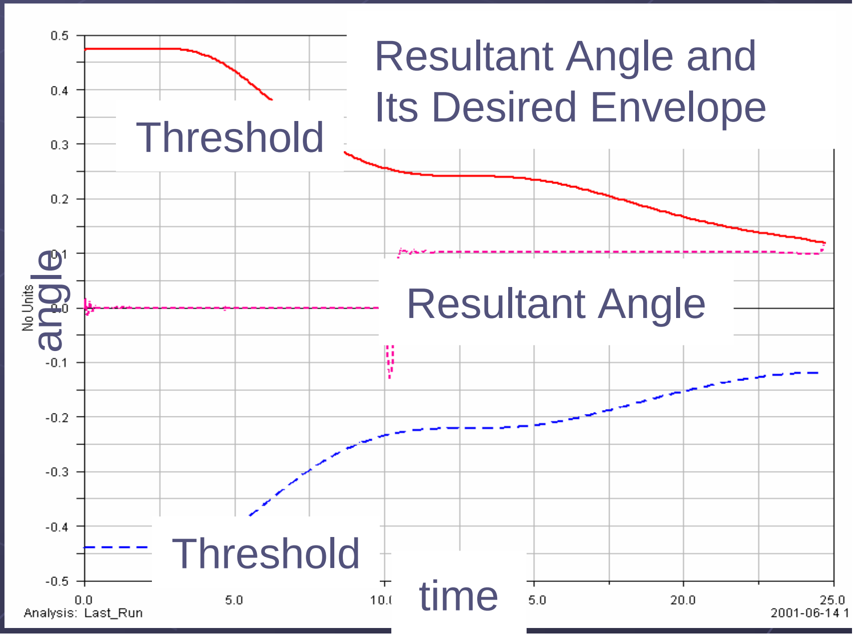
r = position	a = acceleration	ω = ang. velocity	σ = sensor
v = velocity	t = spec. force	α = ang. accel.	c = cg

- Predict specific force that would be observed at the cg.
- Compare to the support polygon
  - Can all be computed in the body frame.

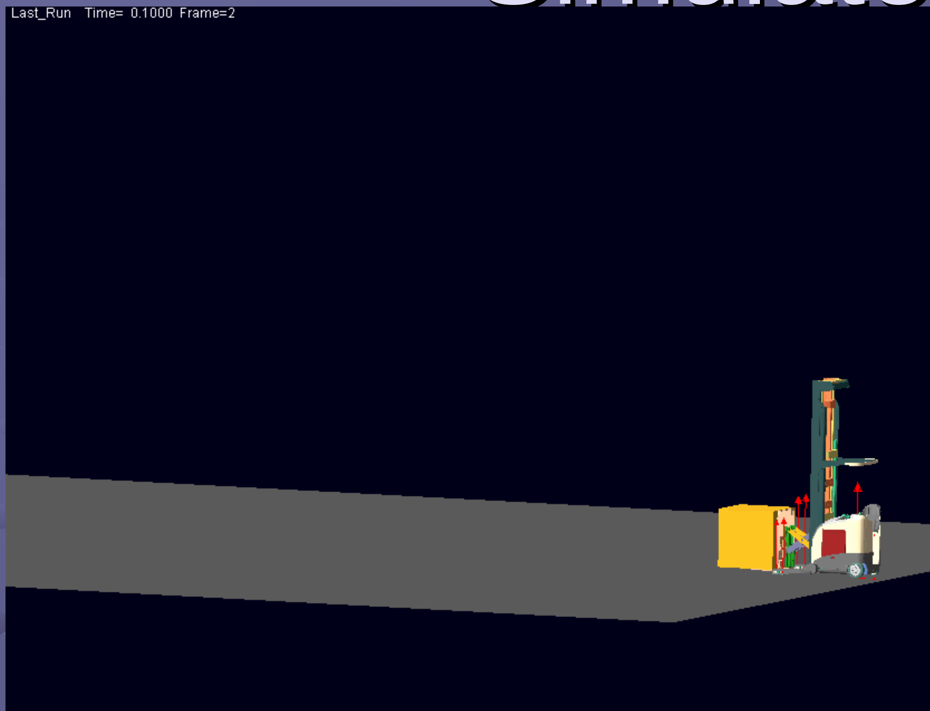
Implementation

- Developed for industrial lift trucks.
- Never put it on a UGV (outdoor robot).





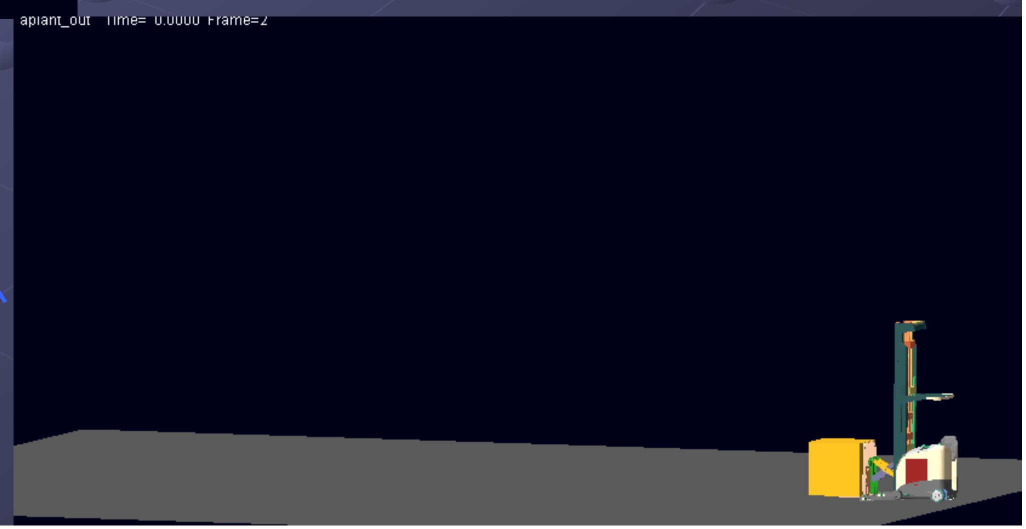
Simulated Result

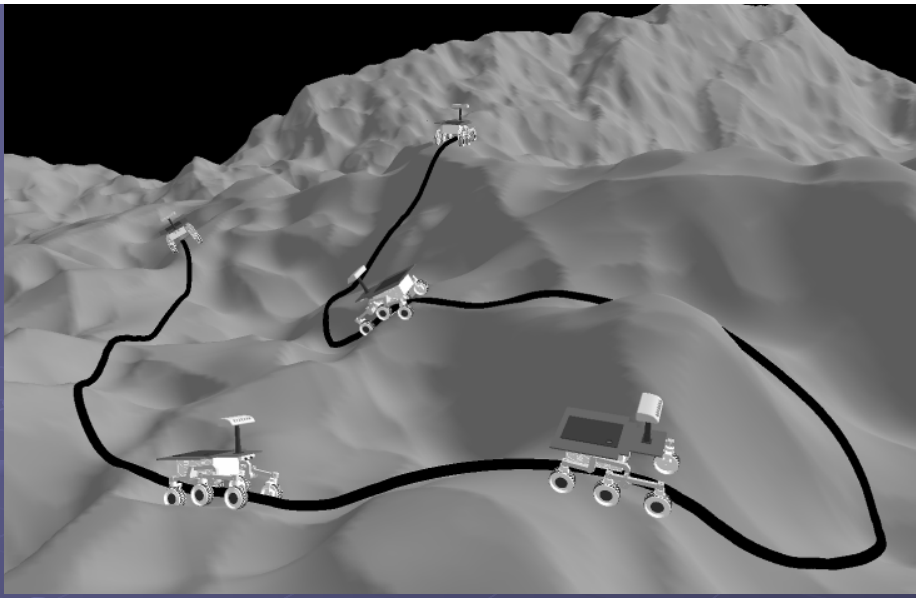


Vehicle without Stability Governor

- Load weight: 3000lbs
- Speed: constant 5mph
- Curvature: constant
- Lift height: 340 inch

Vehicle with Stability Governor





Trajectory Generation

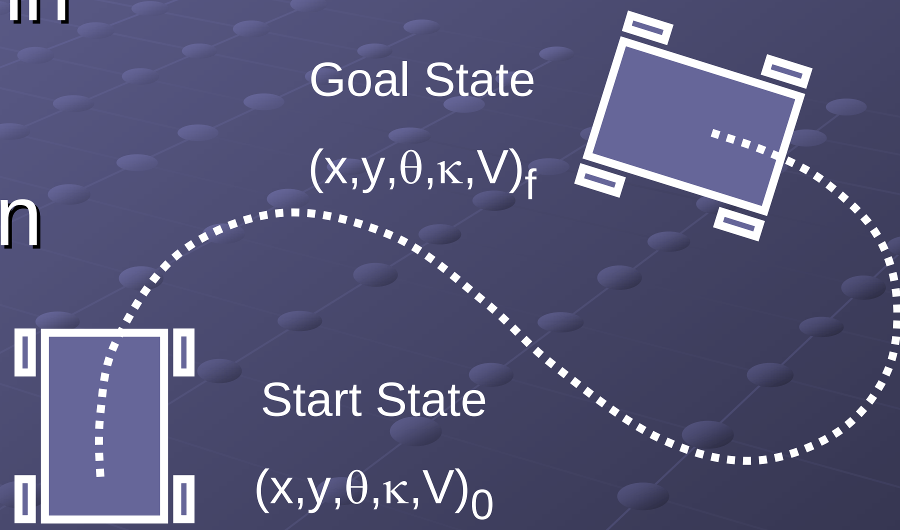
T. Howard, A. Kelly "Optimal Rough Terrain Trajectory Generation for Wheeled Mobile Robots Mobile Robots", to appear IJRR 2006

Philosophy

- High fidelity simulation is routinely used in off road obstacle avoidance.
- Use these existing models in lower level motion control.
  - Becomes the core capacity to move the vehicle.
  - Used by all higher level “planners”.

Numerical Model Inversion

- Terrain is not known in analytic form.
- Terrain following is an important and preditable "disturbance".



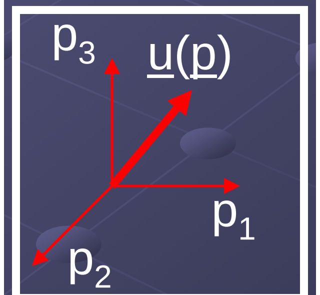
$$\underline{x} \longrightarrow \boxed{\underline{f}^{-1}} \longrightarrow \underline{u}$$

Formulation

Optimal Control		Nonlinear Programming
Optimize $J = \phi[\underline{x}(t_f)] + \int_{t_0}^{t_f} L(\underline{x}, \underline{u}, t)\,dt$	Performance Index	Optimize $J(\underline{p}) = \phi(\underline{p}, t_f) + \int_{t_0}^{t_f} L(\underline{p}, t)\,dt$
Subject to: t_f free	Free duration	Subject to: t_f free
$\dot{\underline{x}} = f(\underline{x}, \underline{u}, t)$	Dynamics	
$\underline{x}(t_0) = \underline{x}_0 \quad \underline{x}(t_f) = \underline{x}_f$	Boundary Conditions	$f(\underline{p}, t_0, t_f) = 0$
$\lvert \dot{\underline{u}}(t) \rvert \le \dot{\underline{u}}_{max}(t) \quad \lvert \underline{u}(t) \rvert \le \underline{u}_{max}(t)$	Input Limits	$\lvert \underline{p} \rvert \le \underline{p}_{max}$

Optimal Control

- A natural formulation with standard numerical approaches for sampled solutions.
- Search a function space.



Nonlinear Programming

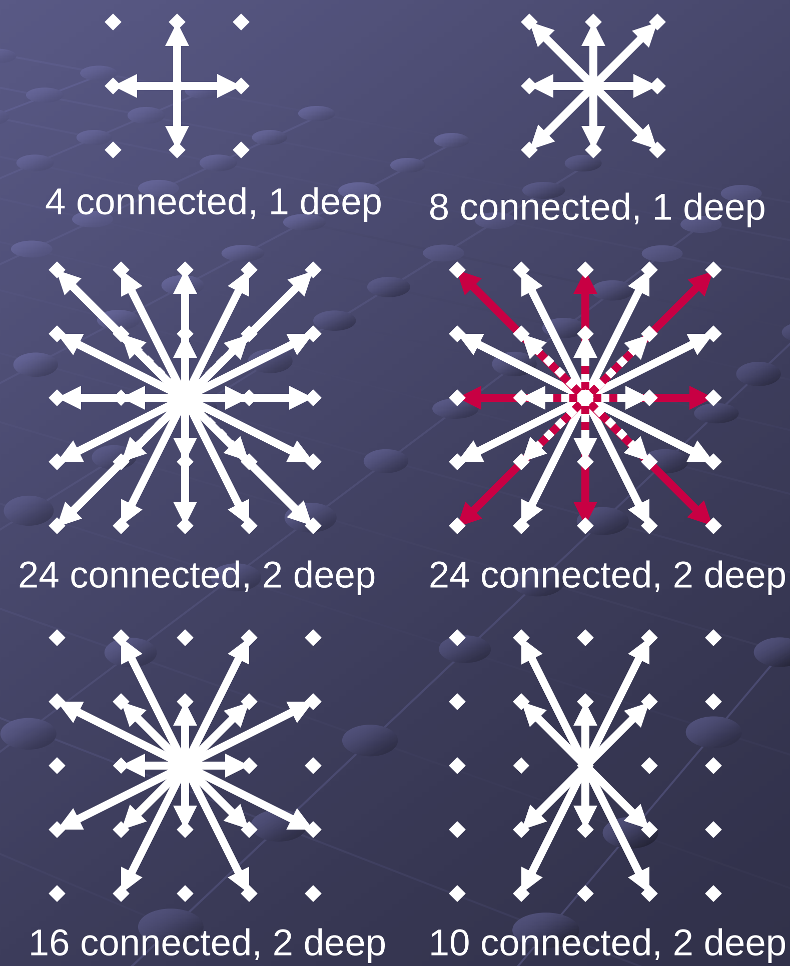
- Easier (less dof) and produces continuous solutions.
- Search a parameter space.

Exploit Full Vehicle Mobility

Corrective Trajectories

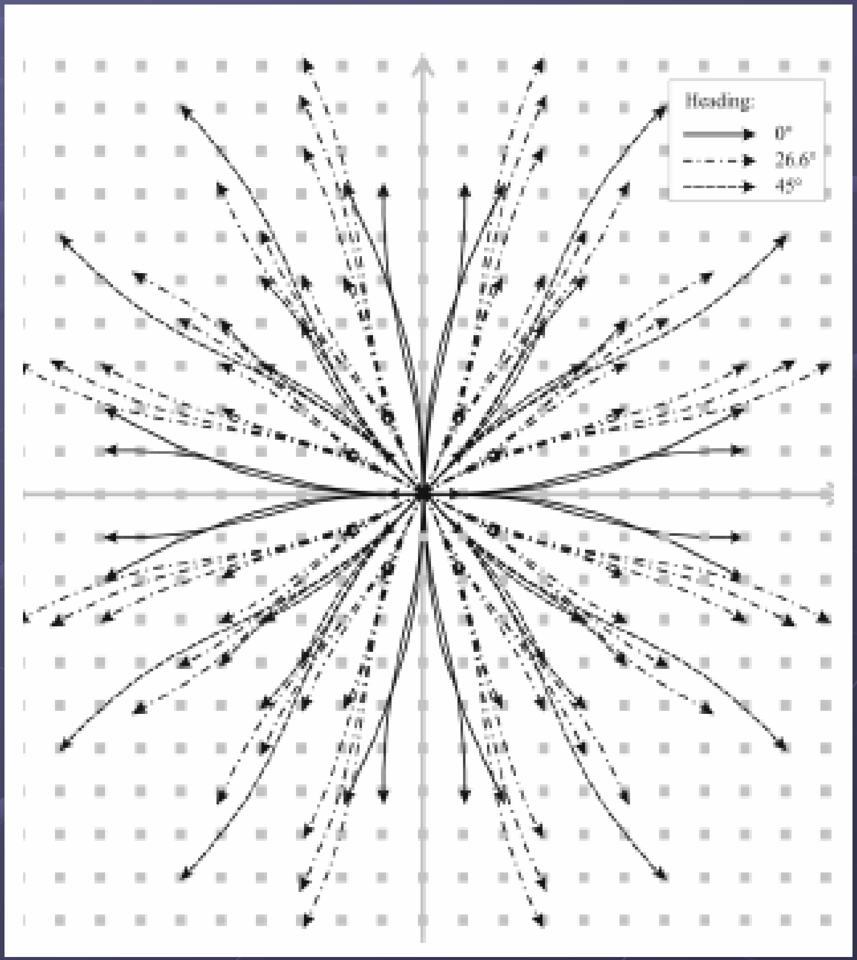
Search Space Design

- States:
  - discretize regularly (lattice).
- Controls:
  - compute connectivity via exact solutions in finite neighborhood.
- Prune controls based on:
  - Redundancy
  - Feasibility



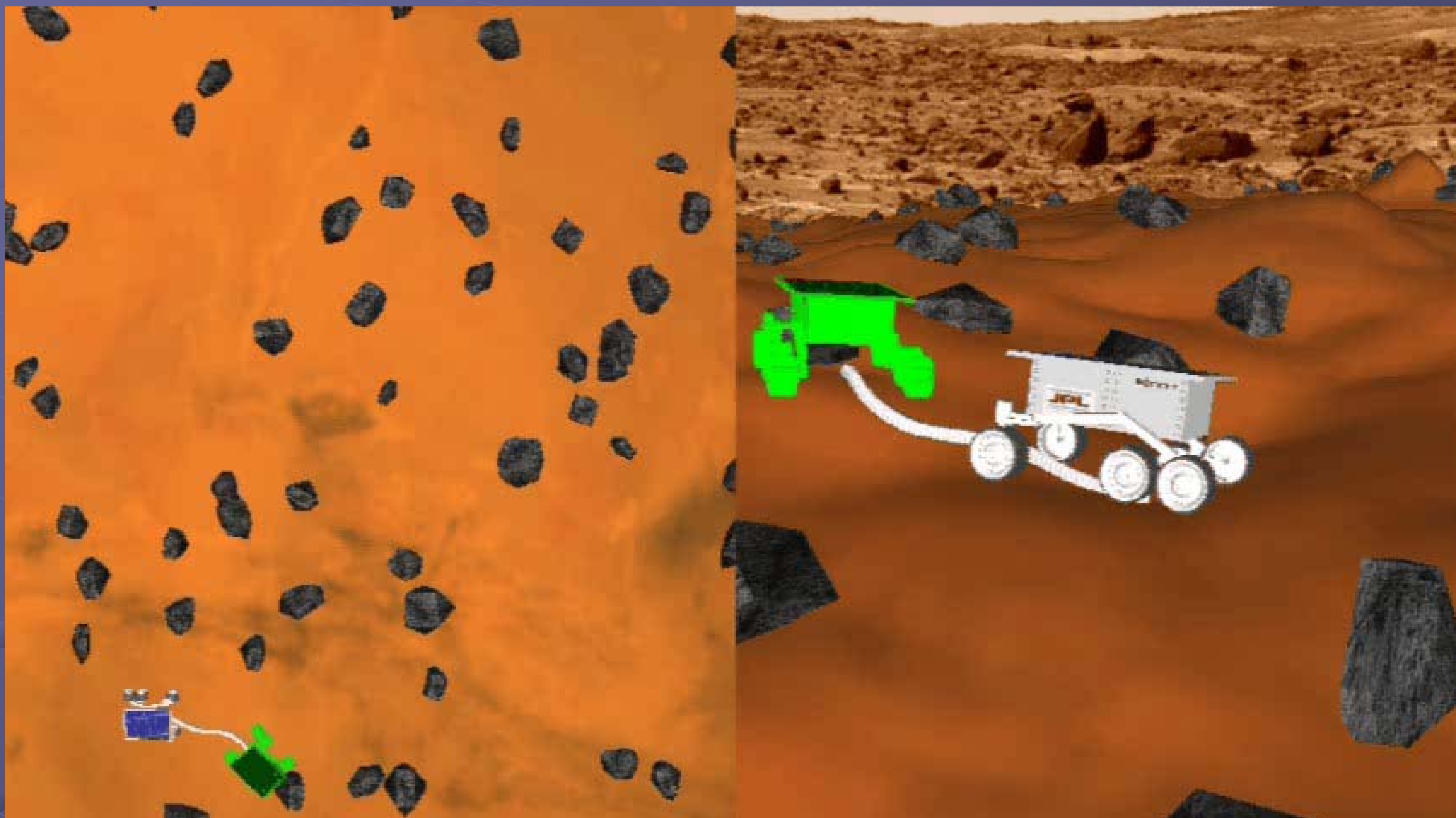
Real Control Set

- Encapsulates the essential connectivity of state space subject to nonholonomic/dynamic etc constraints.
- This can be <u>generated automatically</u> given a trajectory generator.
- This is (implicitly) copied everywhere to generate the search space.

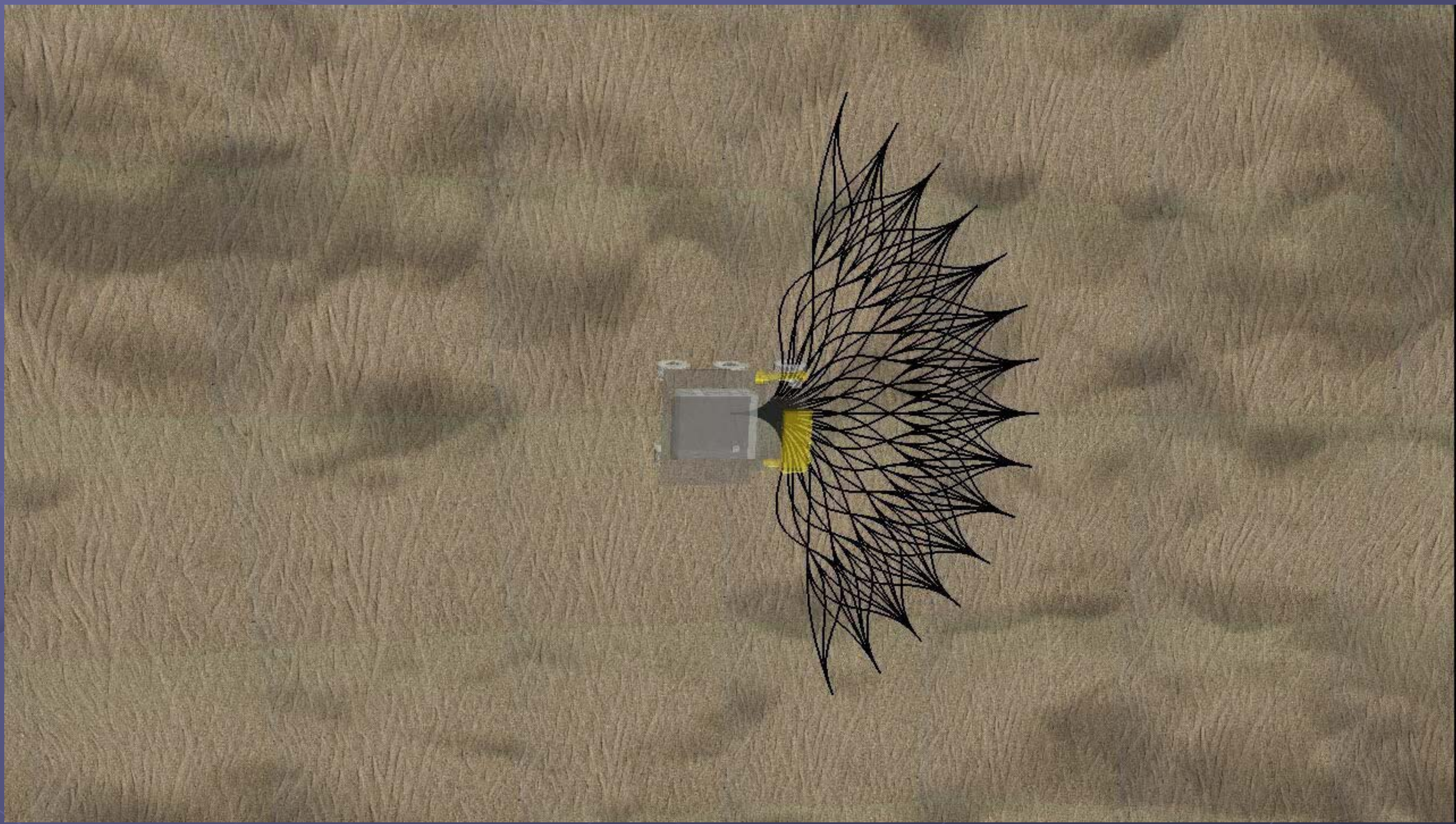


NOTE: All headings shown in one layer

Dense Obstacle Planning



Ego Graphs For Obs Avoidance



Conclusions

- Stability Margin Estimation
  - Its just code!
  - Useful if (when) autonomy fails.
- Trajectory Generation
  - Core capacity to plan end execute any feasible motion.
  - Many planners can be built over top.

Aggressive Maneuvering of Ground Vehicles over Rough Terrain and Uncertain Environments

Key Issues and Possible Approaches

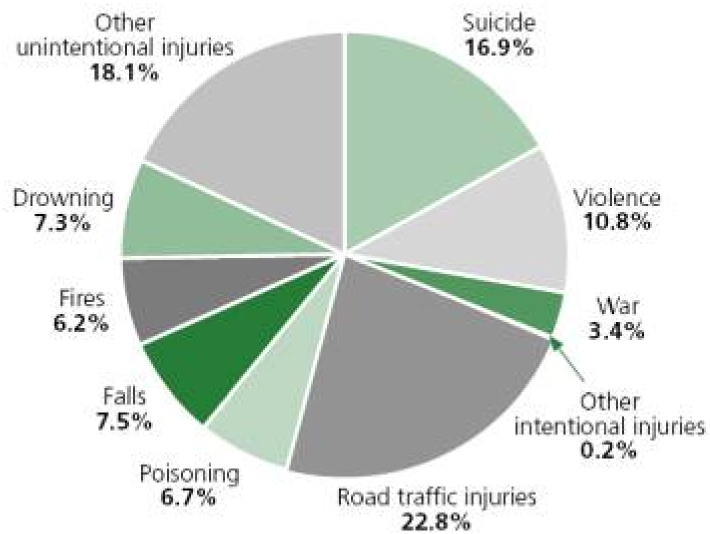
Panagiotis Tsiotras
School of Aerospace Engineering
Georgia Institute of Technology
Atlanta, GA 30332-0150

ARO/MIT Workshop on Mobility and Control in Challenging Environments
Olin College, October 5-6, 2006

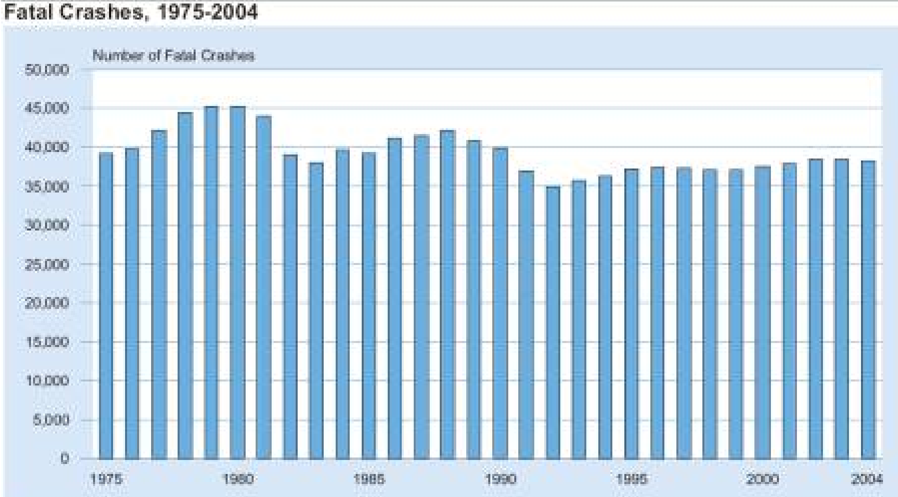
Why Autonomous Vehicles?

- Car accidents result in more than 40,000 deaths and 2,780,000 injuries each year in the US alone
- Car accidents are the leading cause of mortal injuries globally
- Leading cause of death between ages 3-33

Distribution of global injury mortality by cause

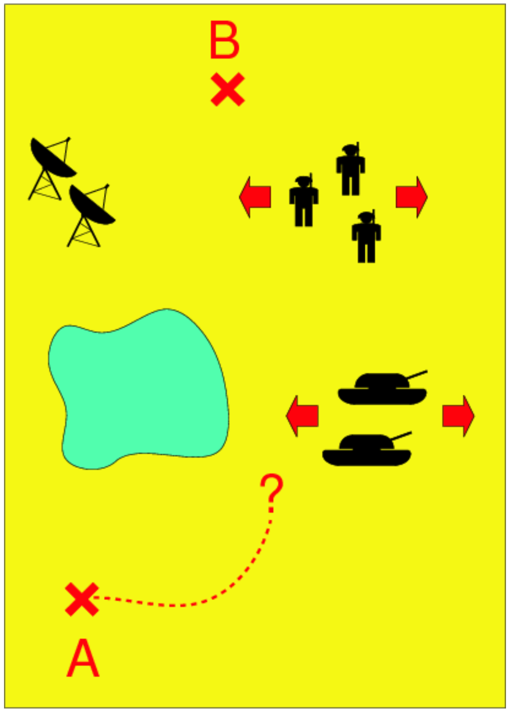


Fatal Crashes, 1975-2004



By 2020, road traffic accidents will be the **3rd leading cause of death** due to injury and disease **combined** (WHO)

Military Applications



- DARPA 2005 GC: 131.2 miles of unpaved course under 10 hours (Mojave dessert)
- Winner (Stanley) average speed 19mph

- Navigation in **uncertain** and **dangerous** environments
- Minimize exposure in danger zone
- **Maximize speed**

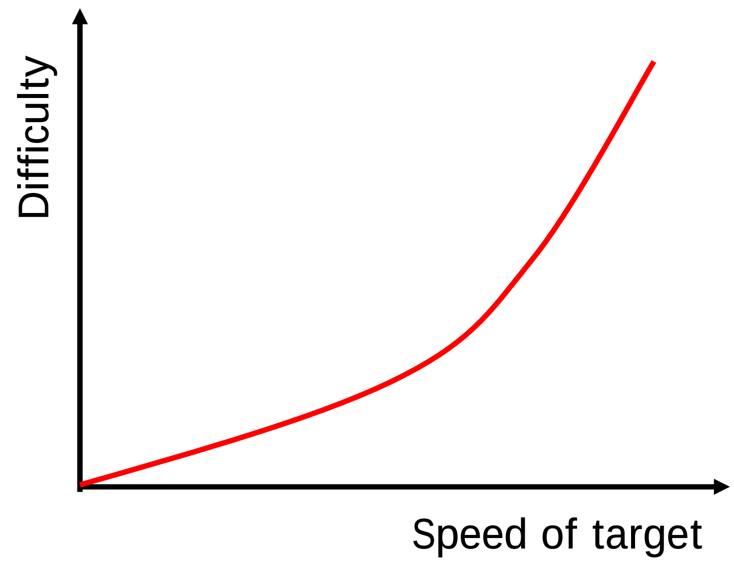
Effect of Speed

- Difficulty to hit a target increases additively with speed.
- As many deaths from vehicle-related accidents as from hostile action.

MVA Deaths	Hostile Deaths
245	3
345	18
337	344
377	737
356	739
1660	1841

2001-2005 Data

- **Driver-assist algorithms** and/or realistic training can prevent this



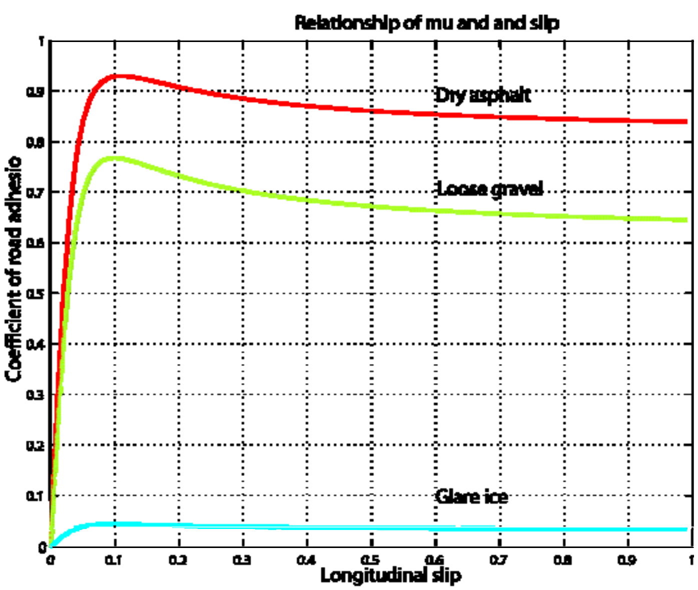
Fast Driving over Rough Terrain?

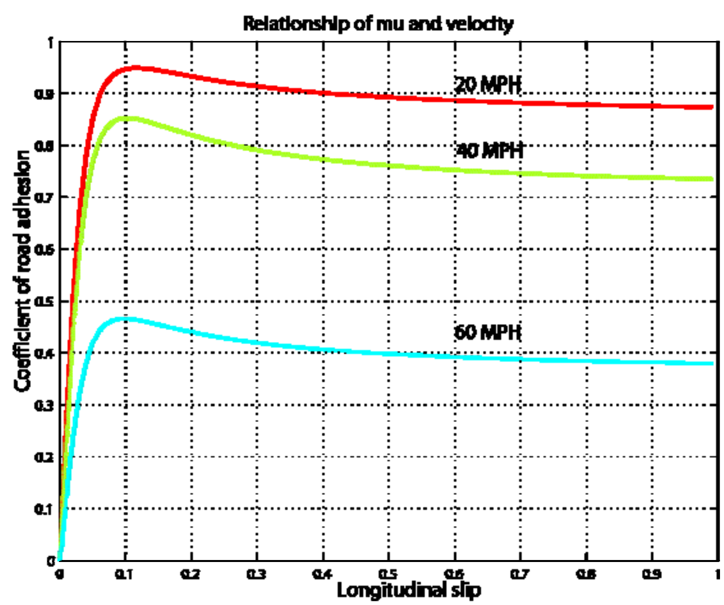
- (Expert) humans do it all the time
- Rally racing
- Rough, loose terrain, ice @ 100mph
- Large slip angles (forget “nonholonomic constraints”)
- Different than closed-track (F1, NASCAR)
- What can we learn from these experts?

Rollover Avoidance?

Friction is Key (what else?)

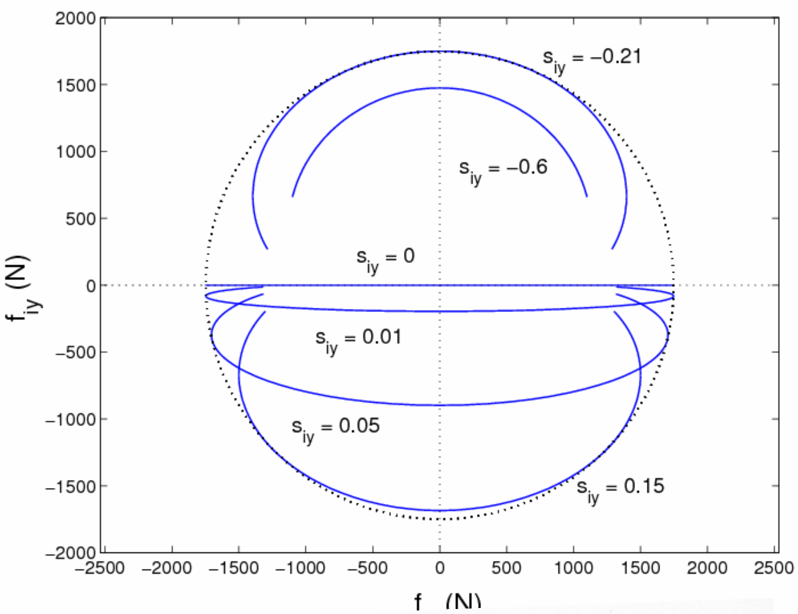
$$\mu = \frac{F}{F_n} = \frac{\text{Friction force}}{\text{Normal force}}$$

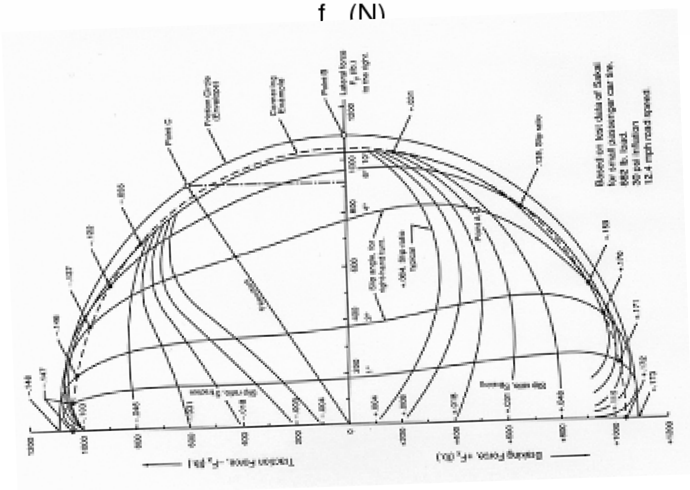




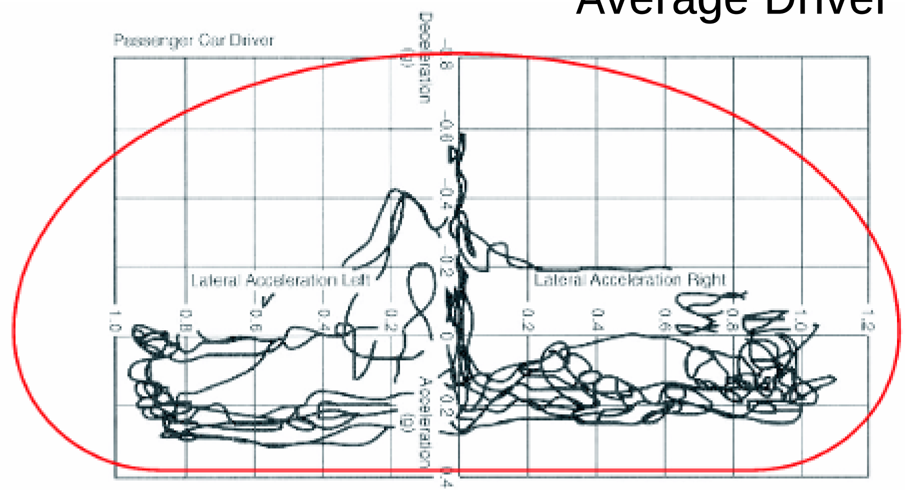
Notoriously difficult to characterize!!

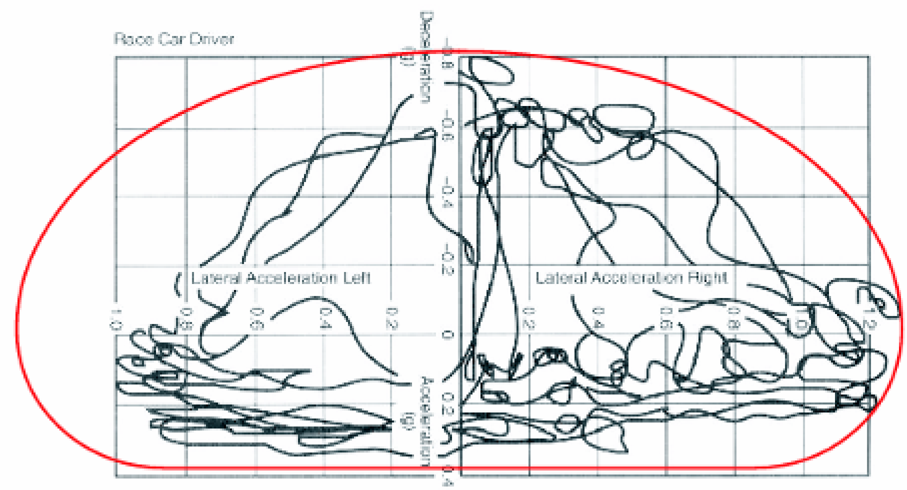
The Friction Circle





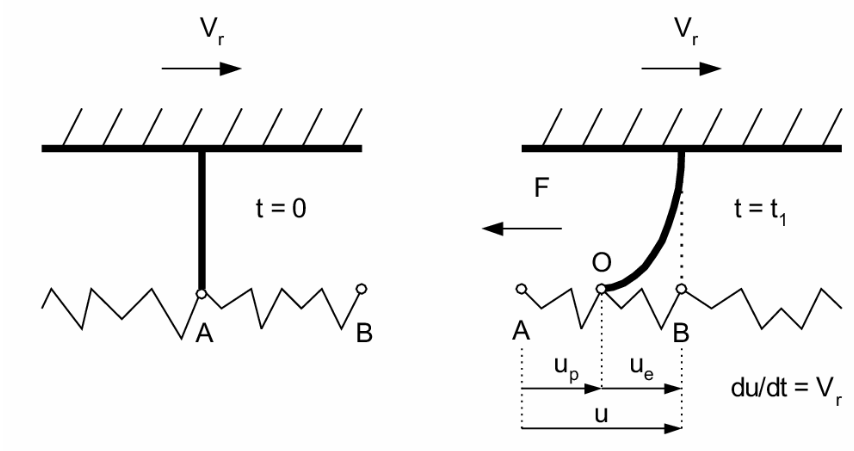
Average Driver

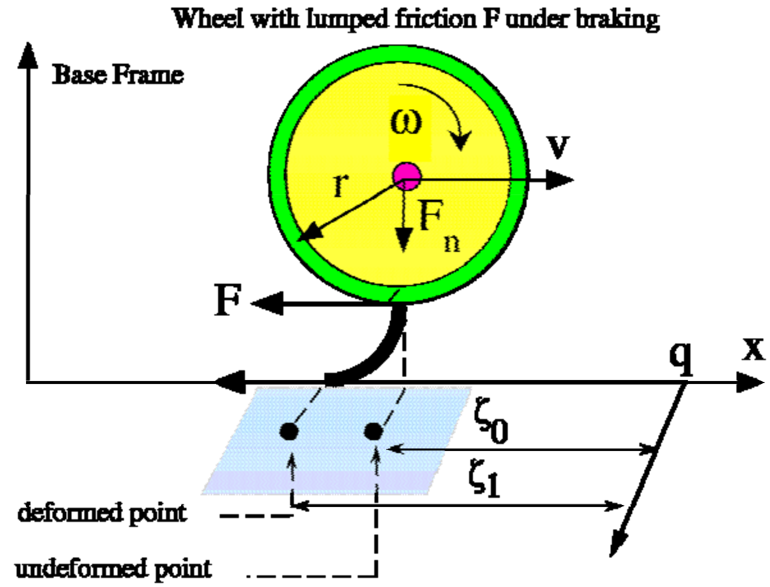




Expert Driver

A Dynamic Tire Friction Model



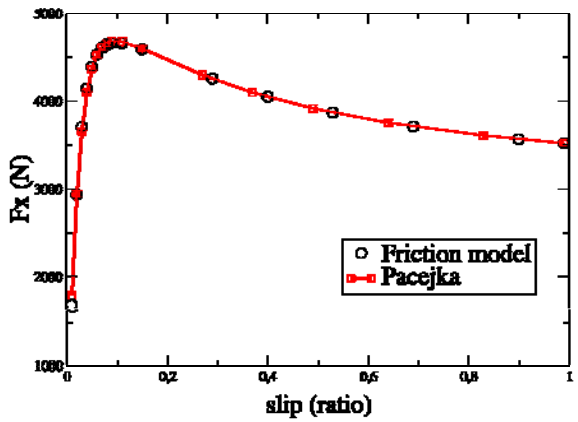


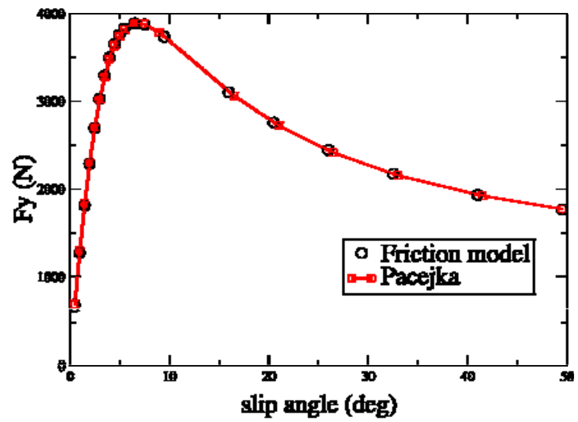
$$
\begin{aligned}
\dot{z} &= v_r - \frac{\sigma_0 |v_r|}{g(v_r)} z \\
F &= (\sigma_0 z + \sigma_1 \dot{z} + \sigma_2 v_r)\, F_n \\
g(v_r) &= \mu_c + (\mu_s - \mu_c) e^{-|v_r/v_s|^\alpha}
\end{aligned}
$$

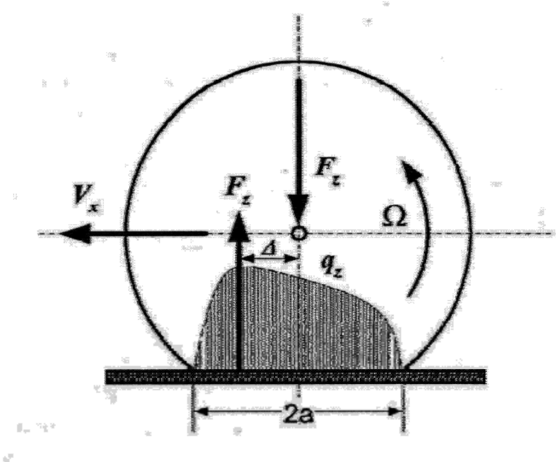
$$
\begin{aligned}
\frac{\mathrm{d}z_i(t,\zeta)}{\mathrm{d}t} &= \frac{\partial z_i(t,\zeta)}{\partial t} + |\omega r| \frac{\partial z_i(t,\zeta)}{\partial \zeta} \\
&= v_{ri}(t) - C_{0i}(v_r) z_i(t,\zeta) \\
\mu_i(t,\zeta) &= -\sigma_{0i} z_i(t,\zeta) - \sigma_{1i} \frac{\partial z_i(t,\zeta)}{\partial t} - \sigma_2 v_{ri}(t) \\
F_i(t) &= \int_0^L \mu_i(t,\zeta) f_n(\zeta) \mathrm{d}\zeta, \quad i = x, y \\
M_z(t) &= -\int_0^L \mu_y(t,\zeta) f_n(\zeta) \left(\frac{L}{2} - \zeta\right) \mathrm{d}\zeta
\end{aligned}
$$

DCSL

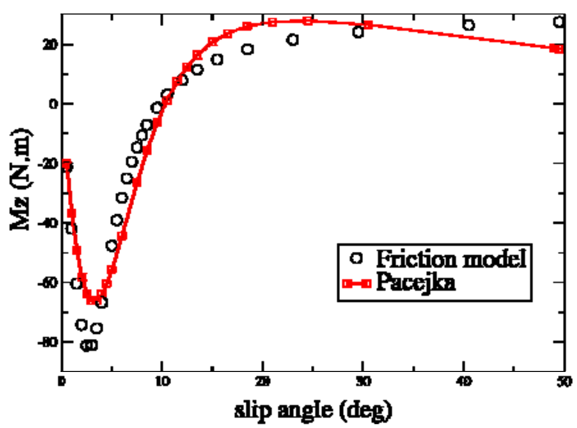
Steady-State







Lumped Model



Captures all conditions
of friction circle

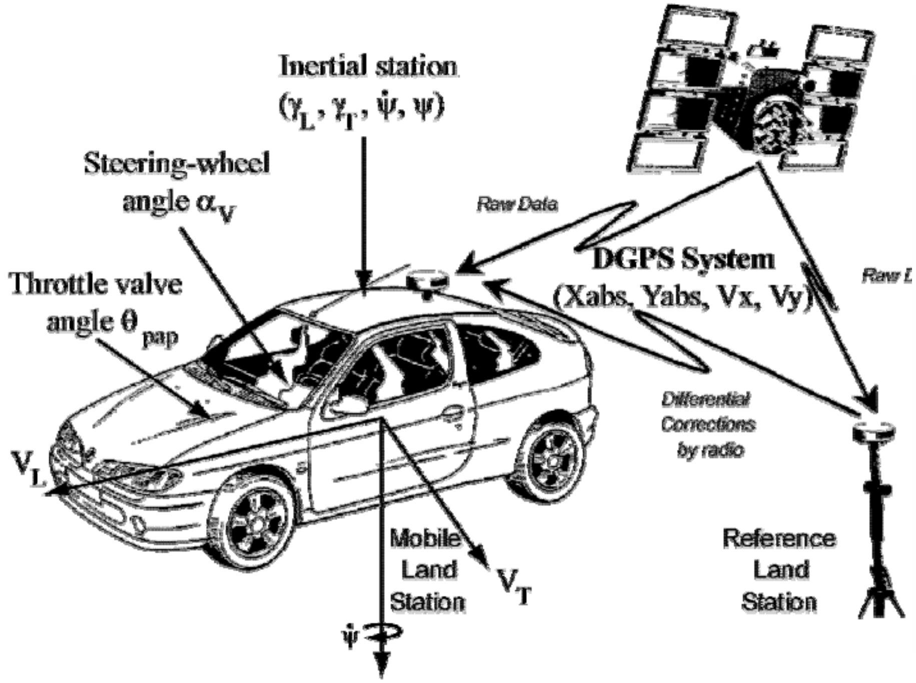
$$\dot{\bar{z}}(t) = v_r - C_0(v_r)\bar{z}(t) - \kappa(t)|\omega r|\bar{z}(t)$$

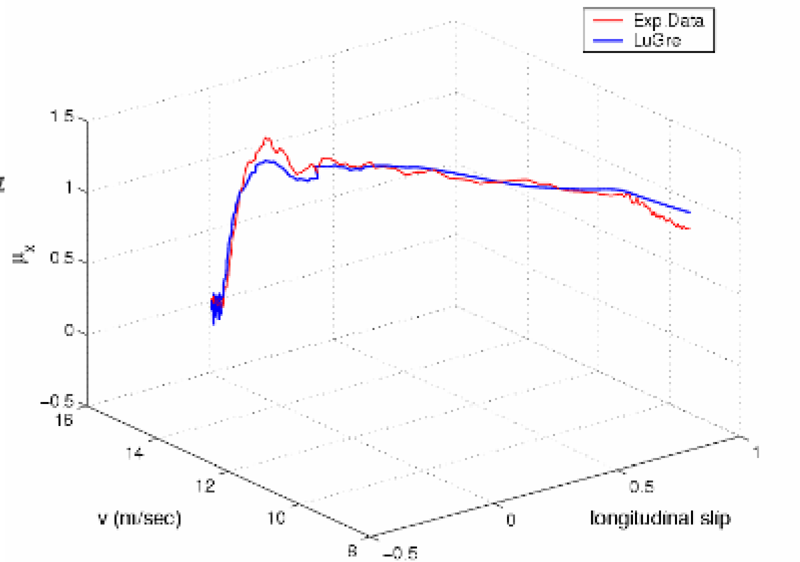
$$\bar{F}(t) = -F_n(\sigma_0 \bar{z}(t) + \sigma_1 \dot{\bar{z}}(t) + \sigma_2 v_r)$$

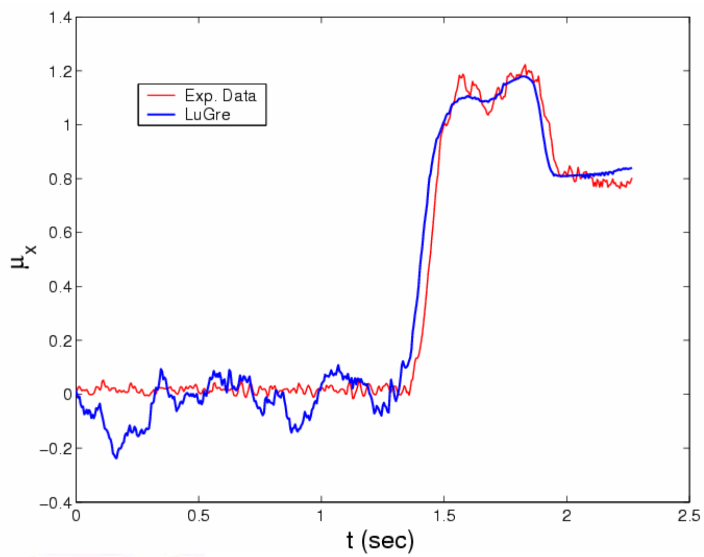
$$C_0(v_r) = \frac{\sigma_0 |v_r|}{g(v_r)}$$

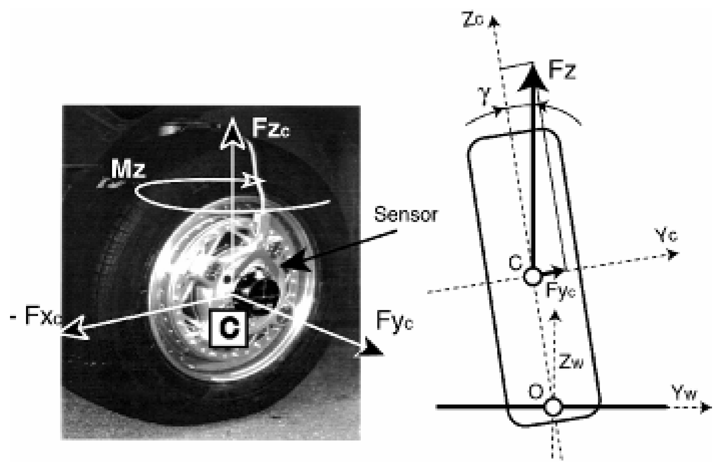
$$\kappa(t) = -\frac{\int_0^L z(t,\zeta) f_n'(\zeta) \mathrm{d}\zeta}{\int_0^L z(t,\zeta) f_n(\zeta) \mathrm{d}\zeta}$$

Experimental Validation



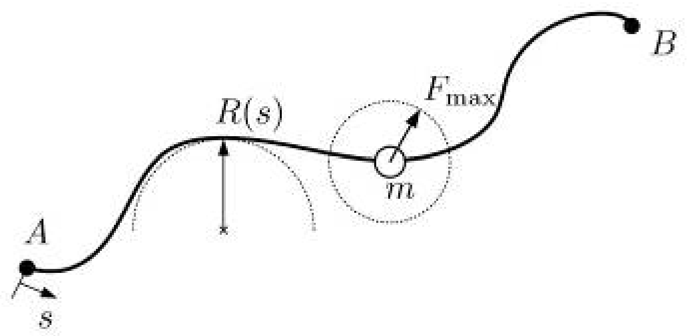






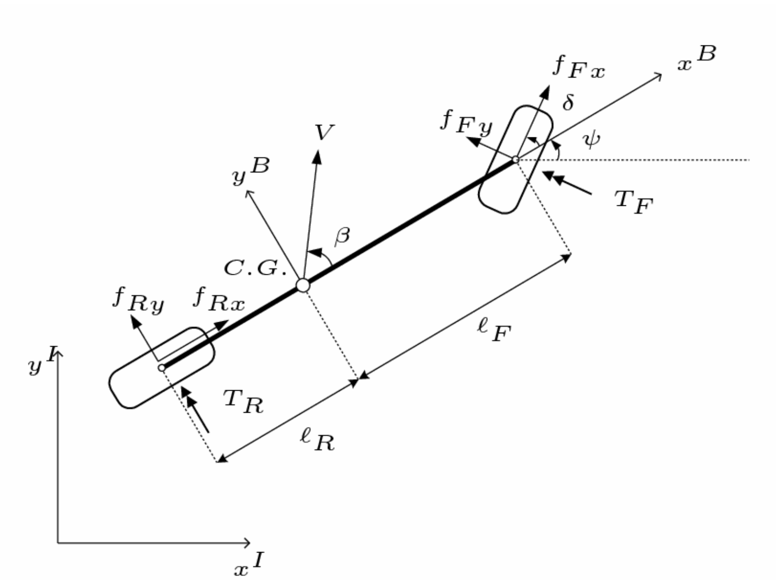
How About Control?

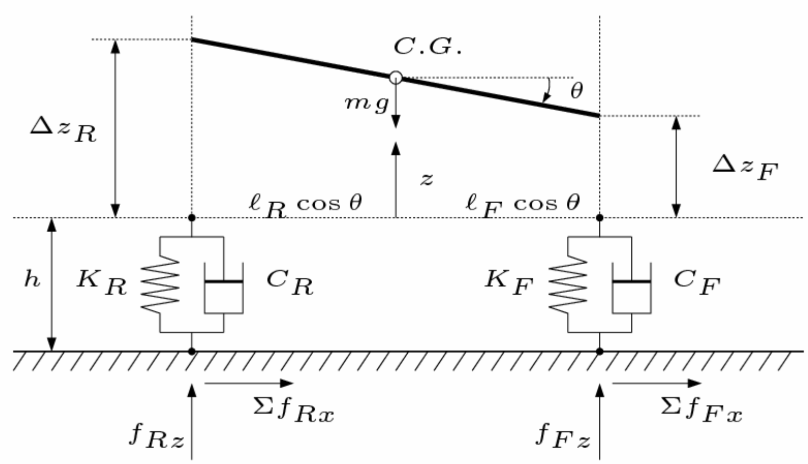
- Assume point-mass model for **velocity control**



$$\dot{z}_1 = z_2,$$
$$\dot{z}_2 = u\sqrt{1-\left(\frac{z_2^2}{R(z_1)}\right)^2}, \quad u \in [-1,+1]$$

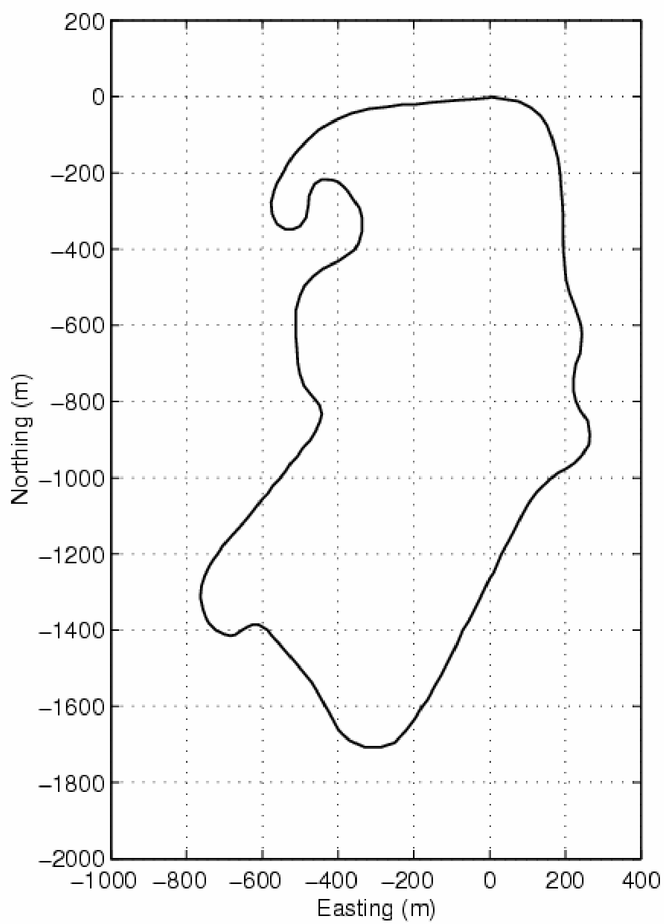
- Assume bicycle model for **posture control** (plus load transfer)

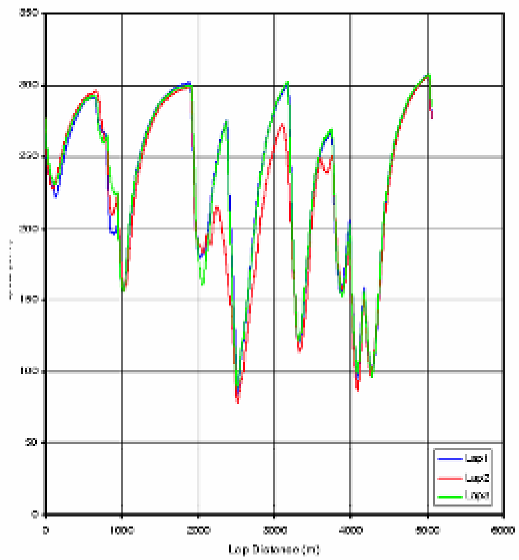


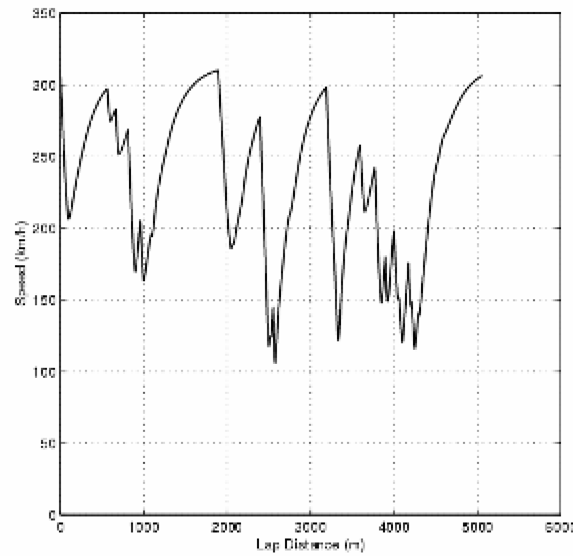


Application to F1

Silverstone



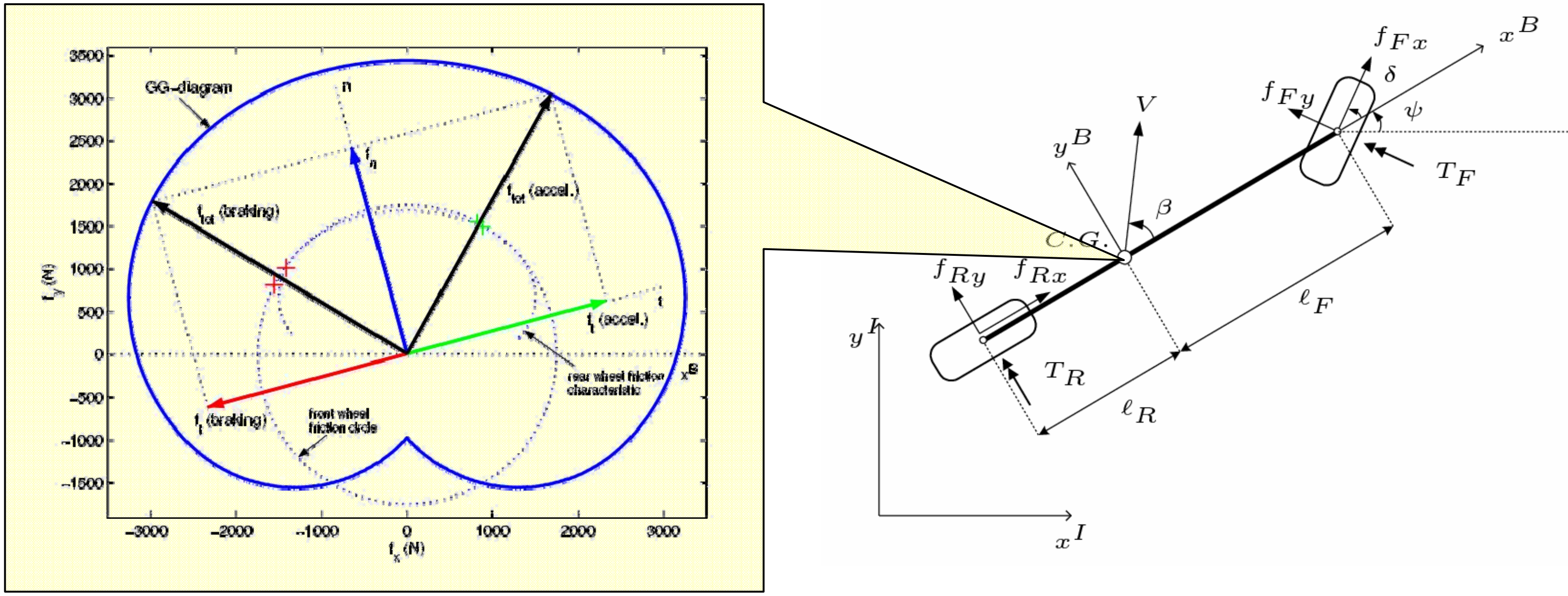




- Measured lap times on given trajectory

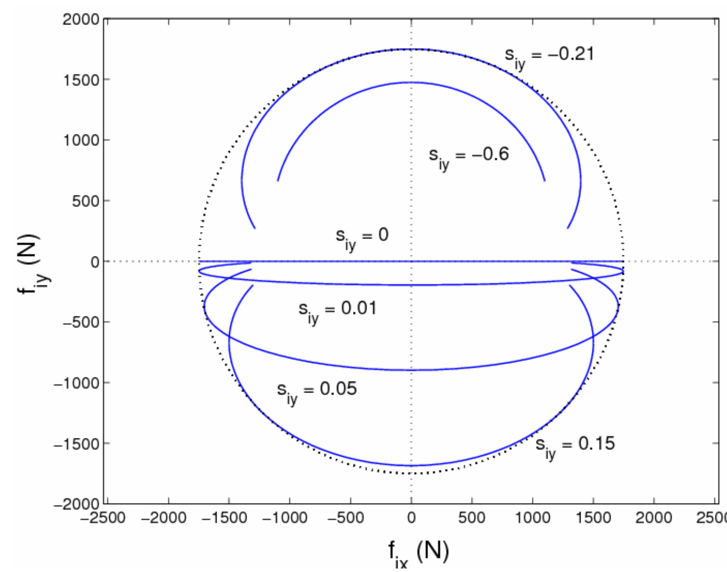
  86.063sec, 90.891sec, 85.805 sec
- Calculated optimal 82.7 sec
- Circuit lap record 78.739 sec (M. Schumacher, Ferrari, 04)
- Circuit record pole 78.233 sec (K. Raikkonen, McLaren Mercedes, 04)

Posture Control



Rear lateral slip determined by vehicle state

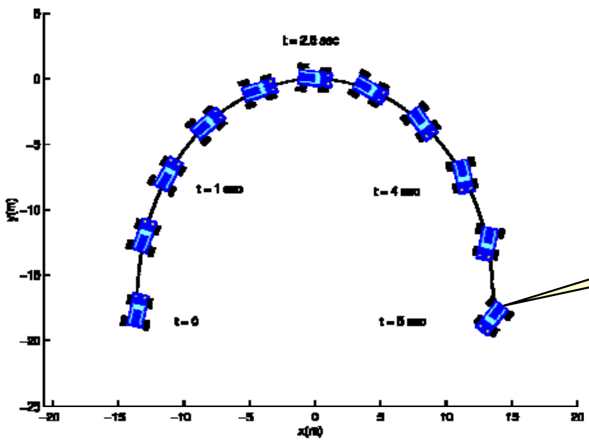
Front wheel may generate any force in the fc



Control Inputs

- front steering angle
- front & rear wheel torque (slip)

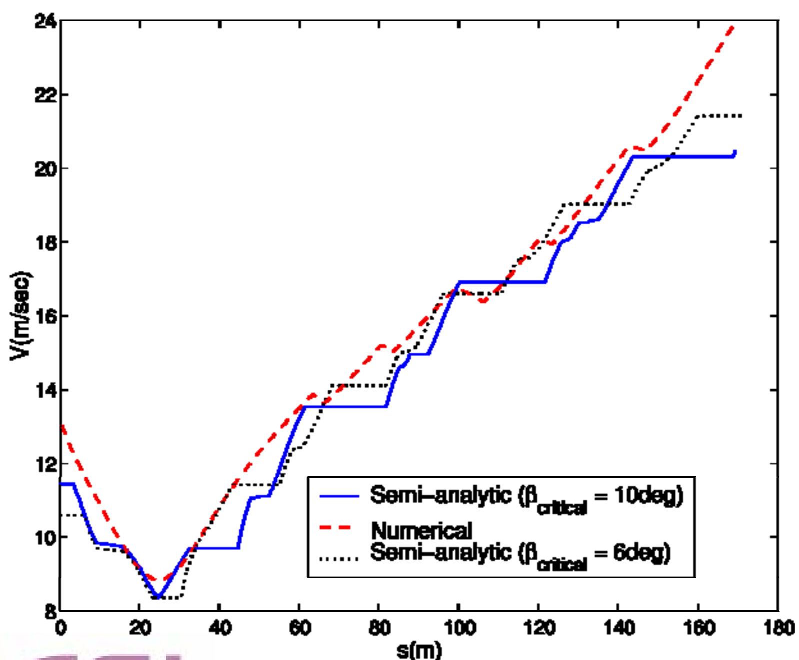
Simulations

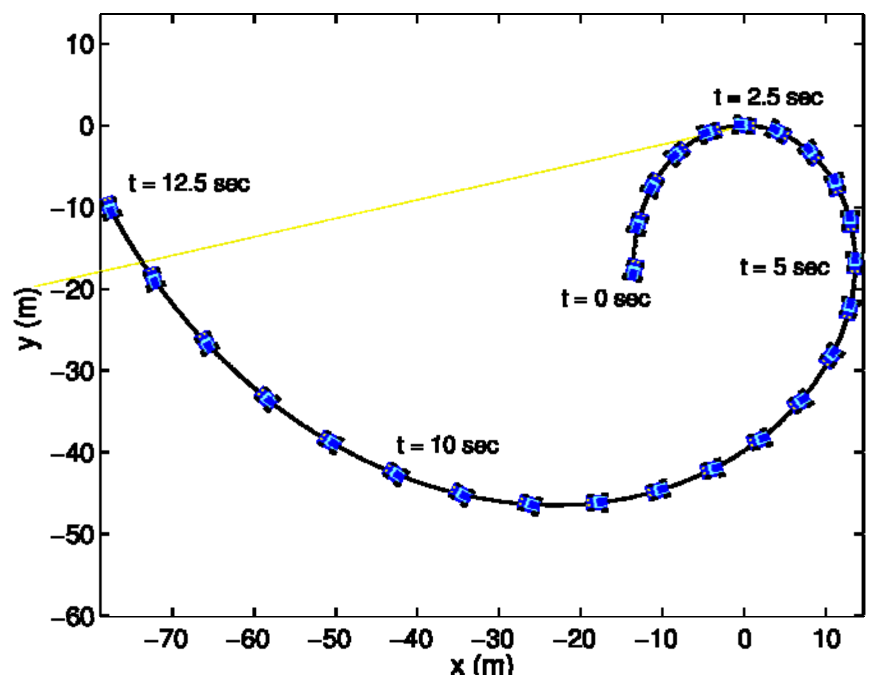


Straightforward application leads to yaw instability

Stabilizing controller to keep β bounded

$$\mathrm{sgn}(\phi')\ddot{\beta} < 0 \text{ if } \beta > \beta_{\mathrm{crit}}$$

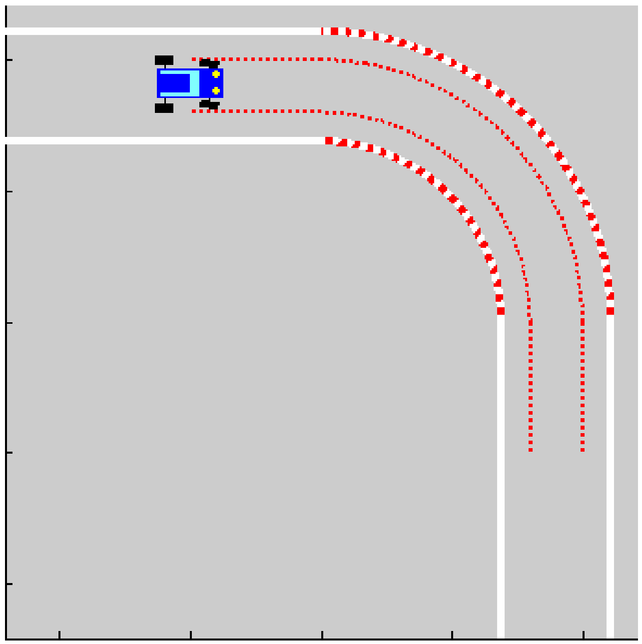




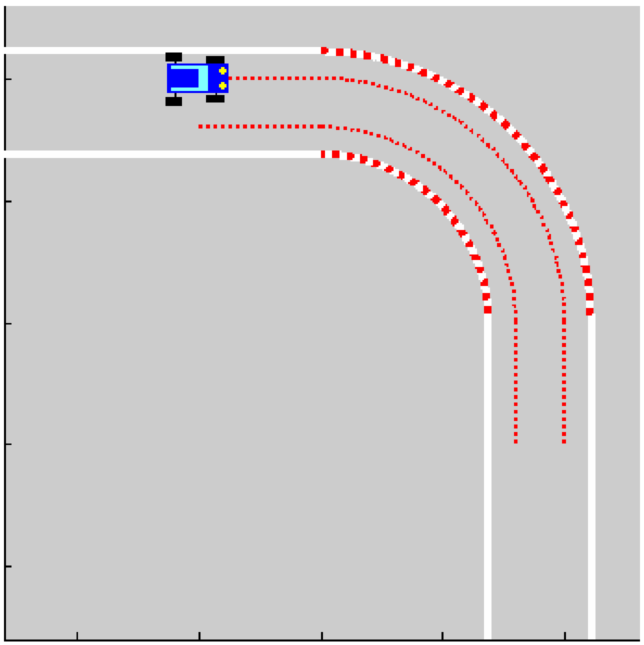
Aggressive Maneuvering

- What cost does the race driver tries to minimize/maximize?
- Minimum-Time, Maximum-Speed, or ...?

Minimum Time

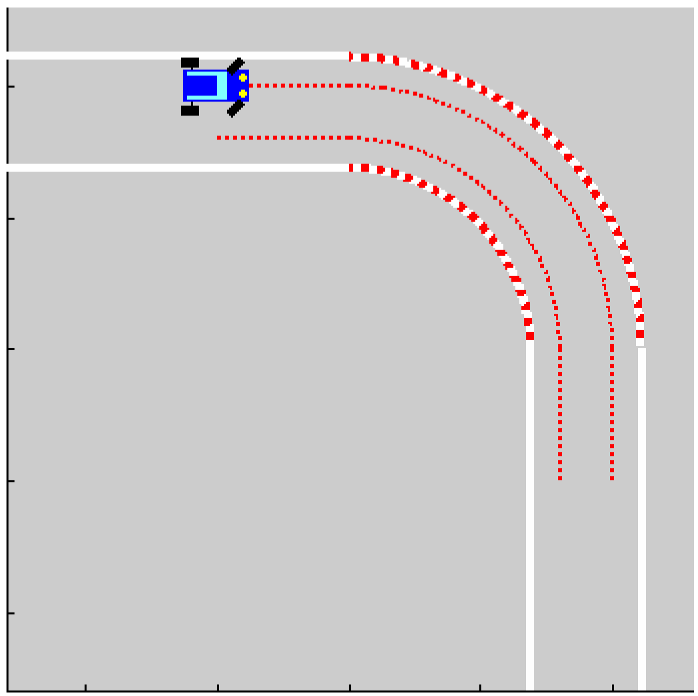


Maximum Exit Velocity



Skidding can be Optimal

Maximum Exit Velocity



A Menagerie of Maneuvers

Technique	When is it used?	Driver's actions
Left Foot Braking (LFB)	When weight transfer from front to rear axles and vice versa is required	Simultaneous application of throttle and brakes to fine tune the distribution of torque between front and rear axles
Slide Turning (Normal Drift)	Entering fast on a wide turn; need to yaw fast	Short application of brakes while cornering to initiate sliding; straighten wheels and stop braking once sliding; accelerate when aligned to the exit
Trail Braking	When carrying too much speed entering a turn; need to yaw fast	Brake hard before corner; start steering while slowly releasing brake
Pendulum (Scandinavian Flick)	Extremely tight corners; normal drift not enough	Initial slide to the opposite direction of the corner to reduce speed as necessary; turn into the corner accelerating fast and LFB to control understeer.
Handbrake Cornering	Tight turns and not enough space for the pendulum mode	Apply handbrake to reduce rear wheel side traction; initiate drift by turning the steering wheel.
Power Oversteer	Slide for a RWD vehicle	Accelerate hard to reduce rear wheel side traction; initiate drift by turning the steering wheel.

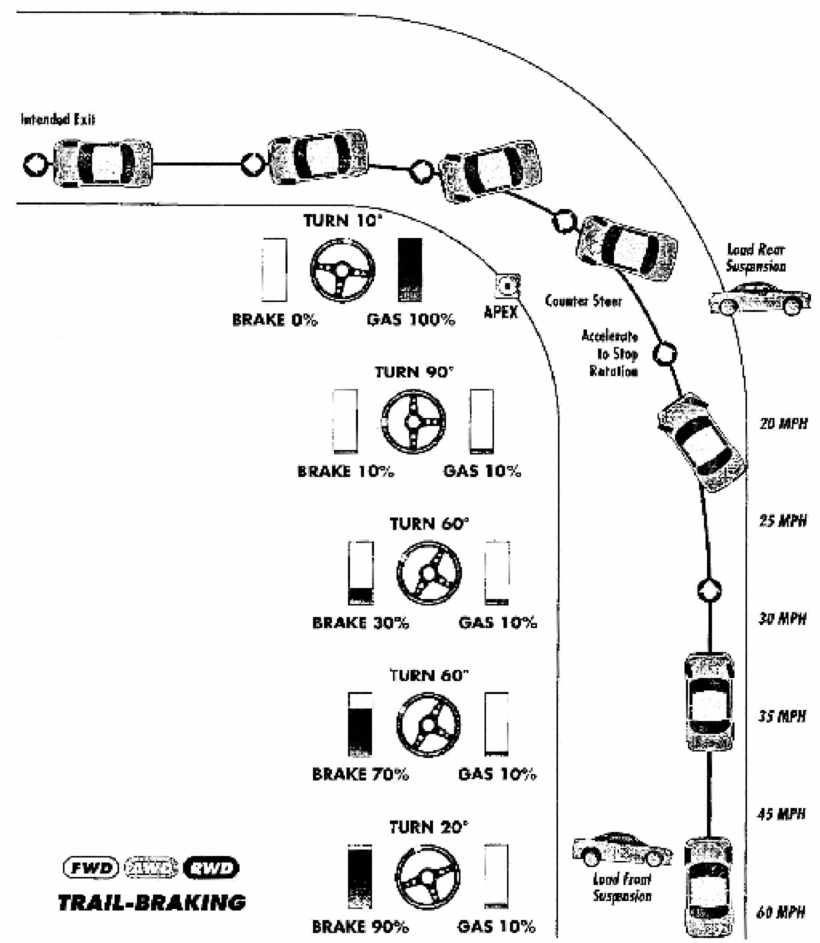
NOTE:

Load transfer extremely important

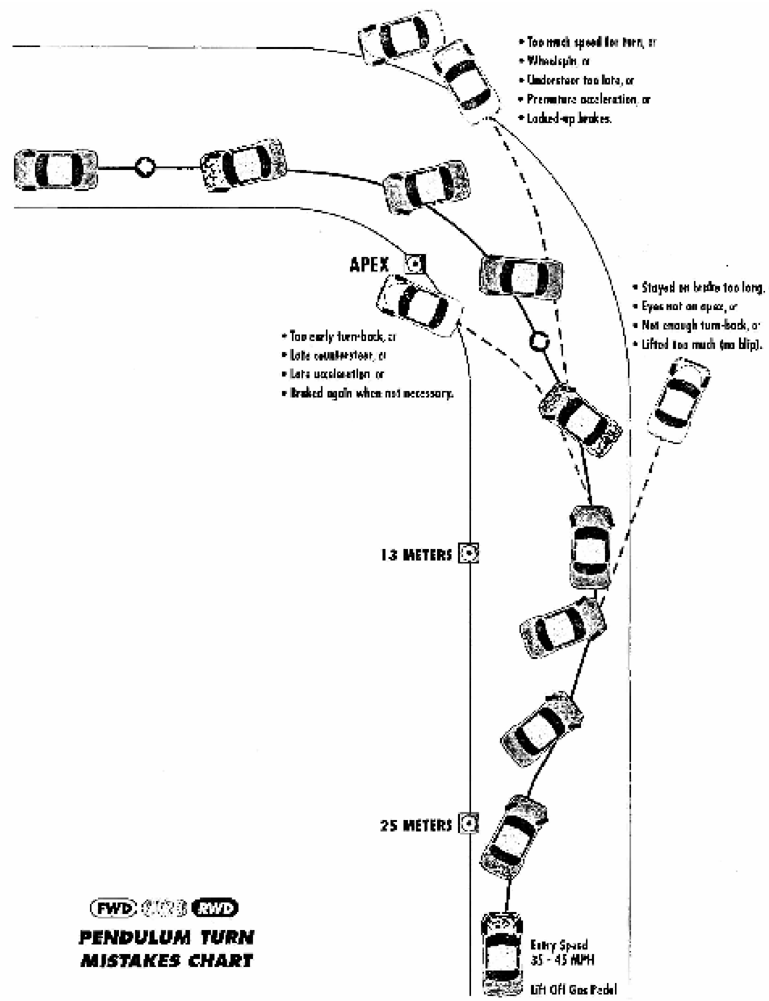
Fine tuning of accelerating/brake torque

Two Examples

Trail-Braking



Pendulum

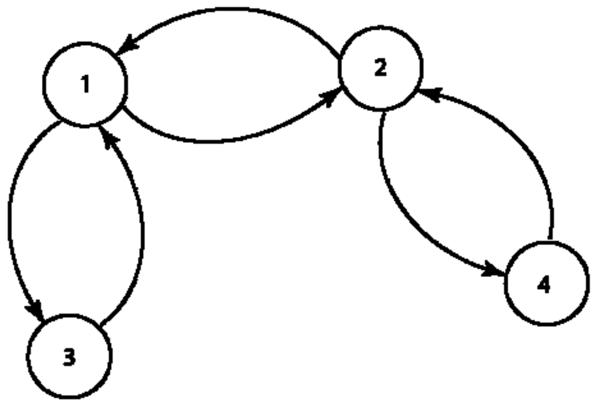


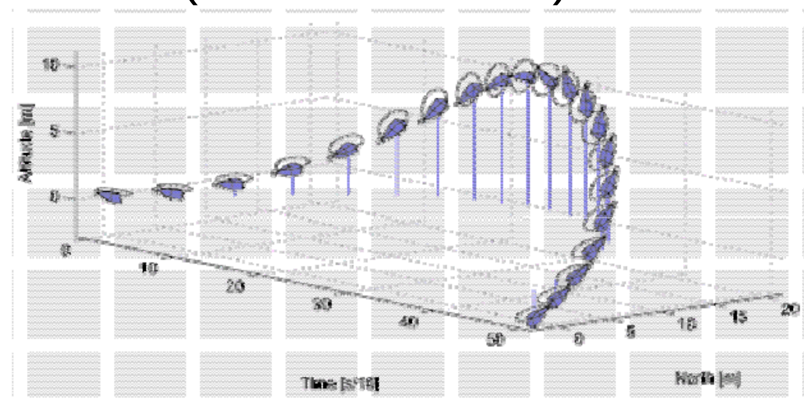
Trail Braking

Pendulum

A Natural Approach

- Construct a library or maneuvers
- Schedule them via a **maneuver automaton** (ala' Frazzoli et al)





$$m^{\star} = m_1 \circ m_3 \circ m_1 \circ m_2 \circ m_4 \circ \cdots$$

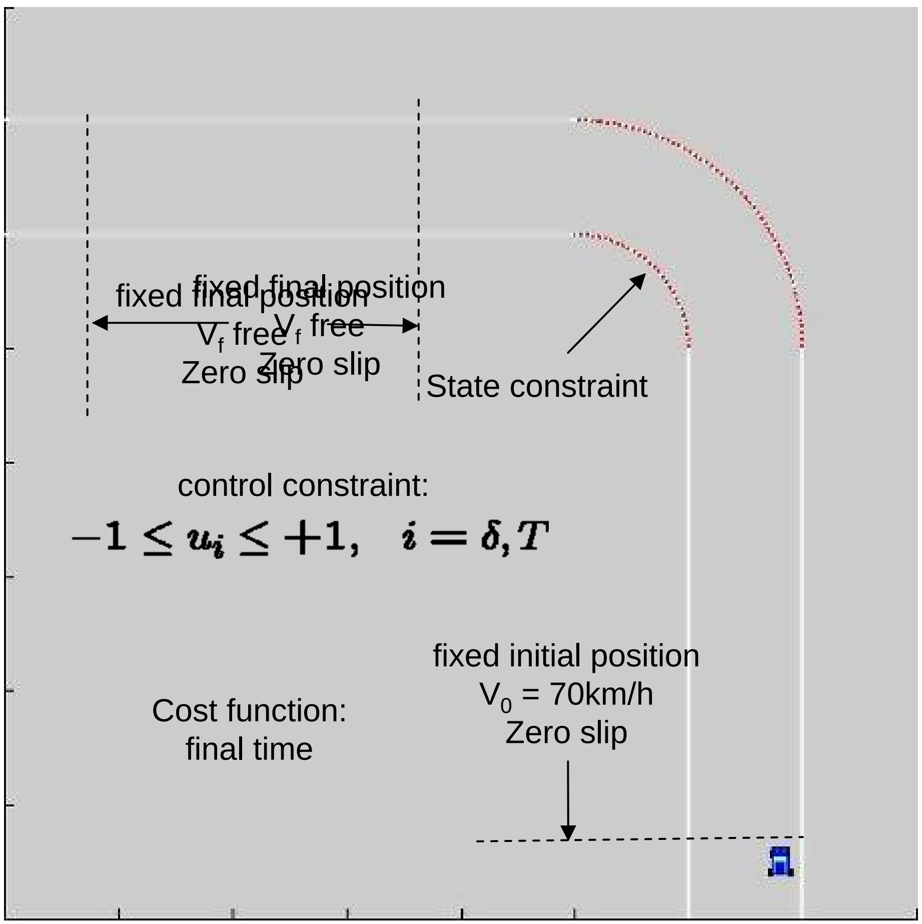
Advantages

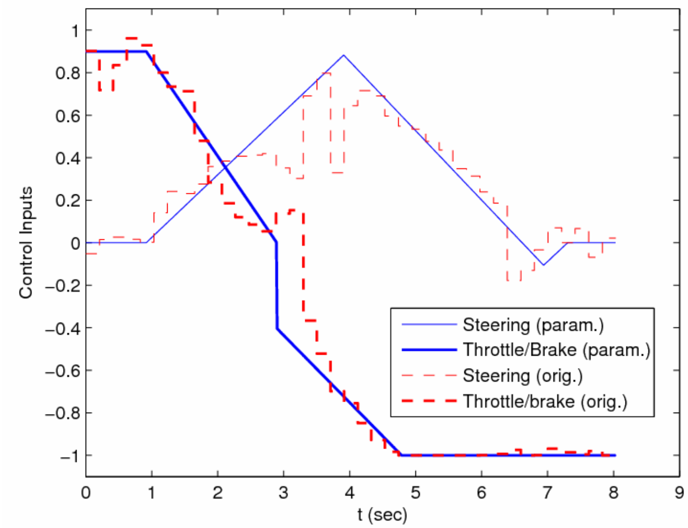
- Easy to implement
- Mimics expert race driver

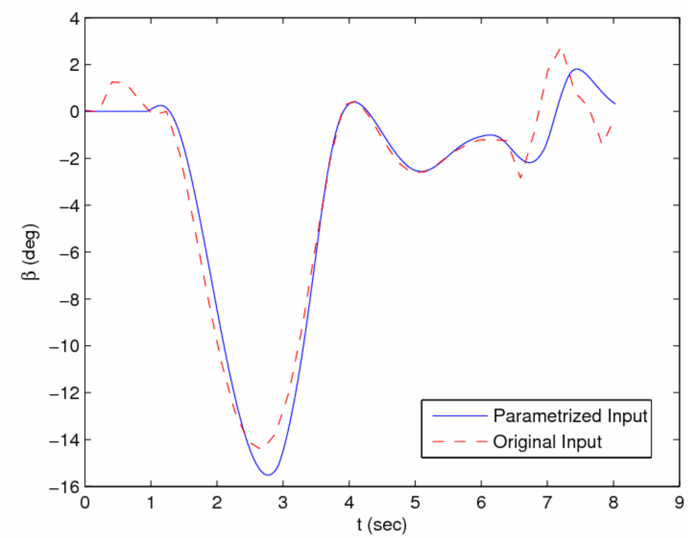
Challenges

- Need a good parameterization
- Robustness
- Triggering (environmental awareness)

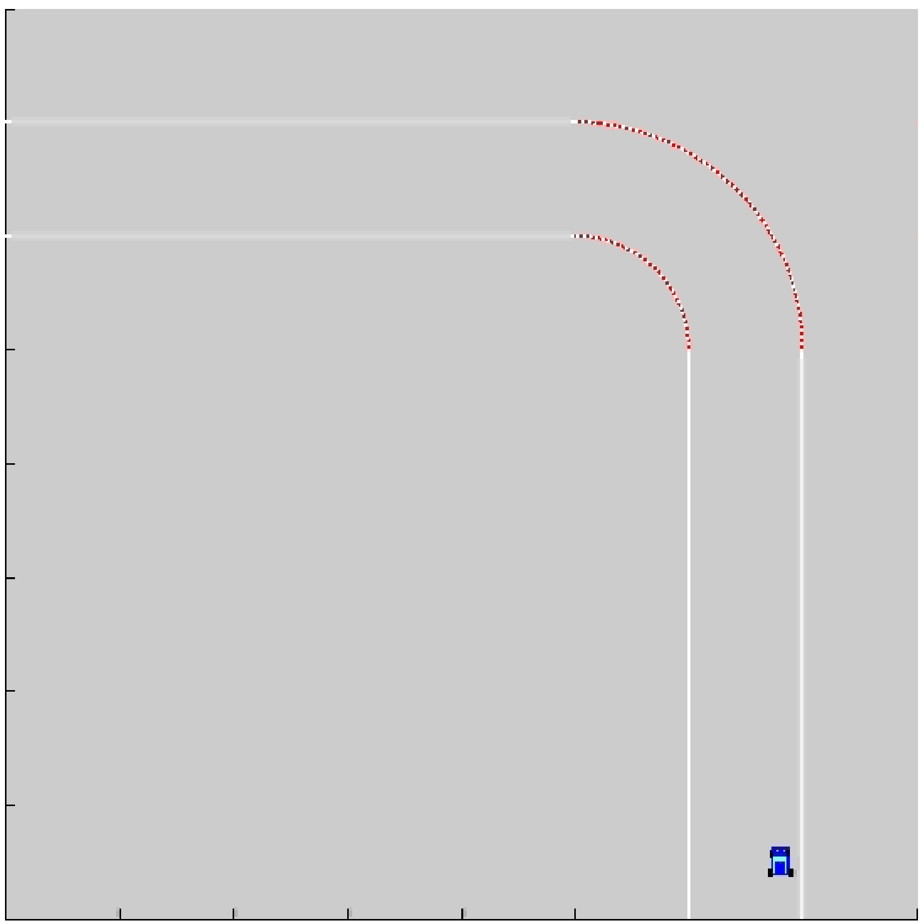
Case Study: TB

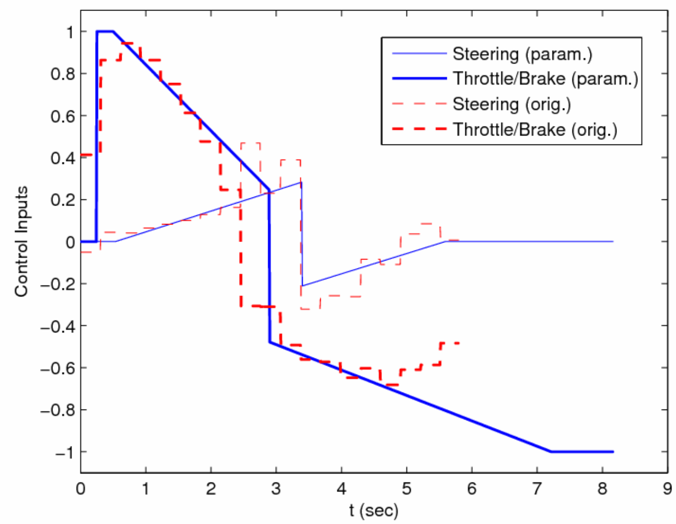


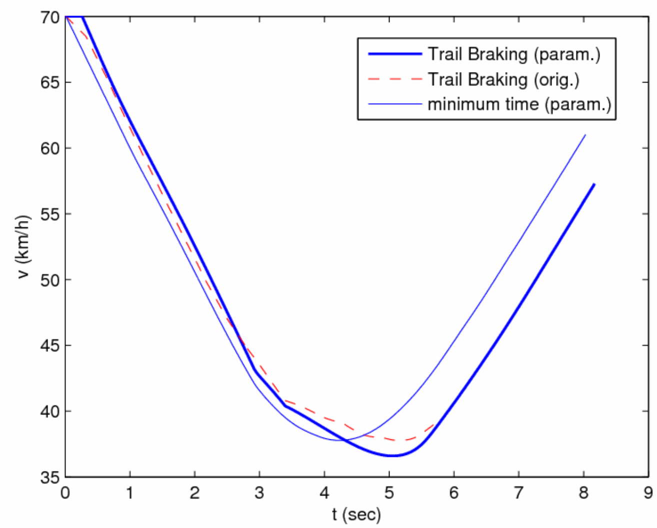




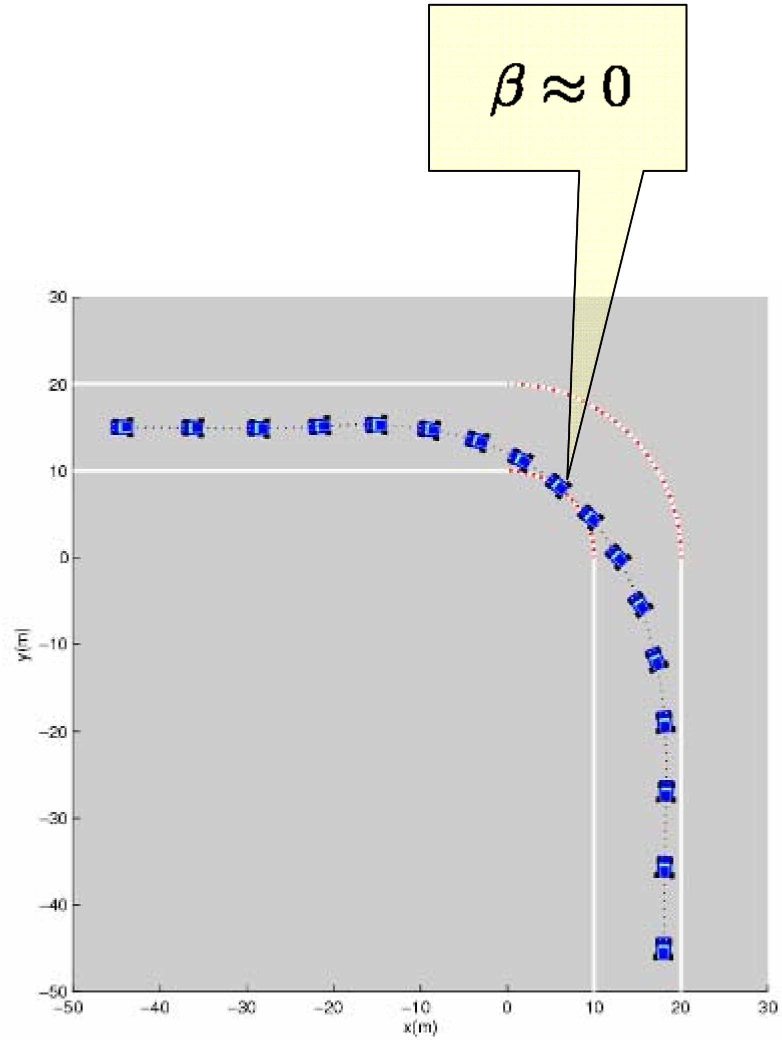
Case Study: TB



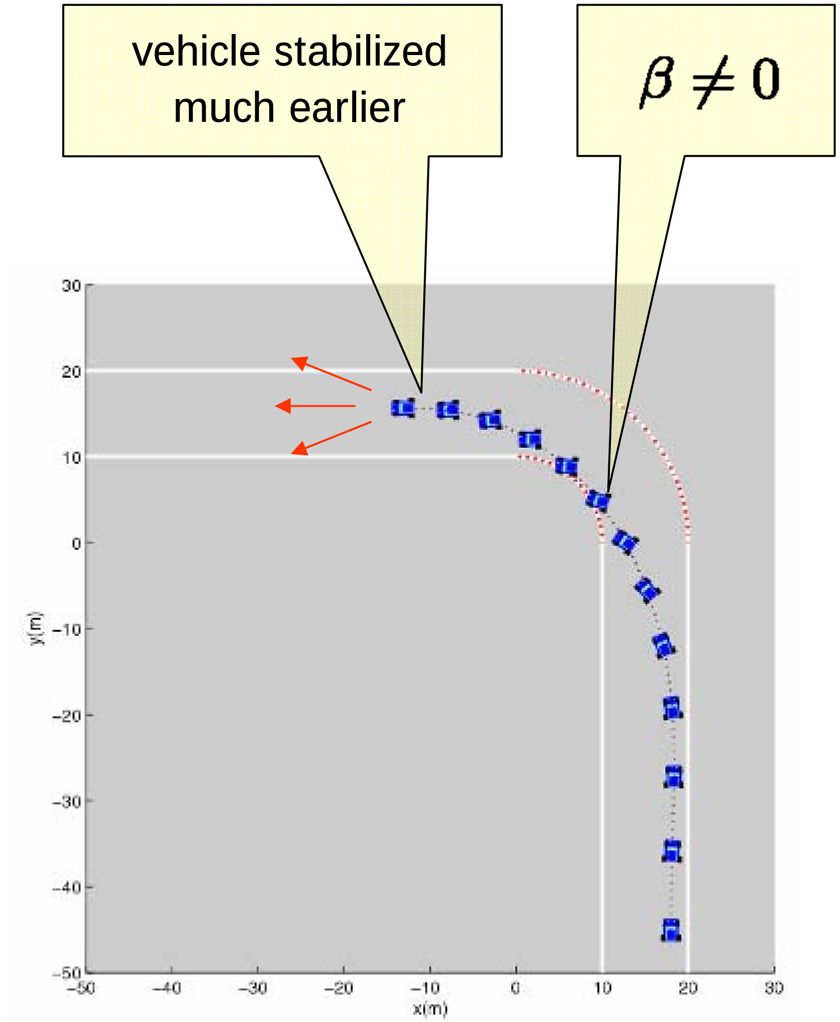




Comparison



Minimum Time

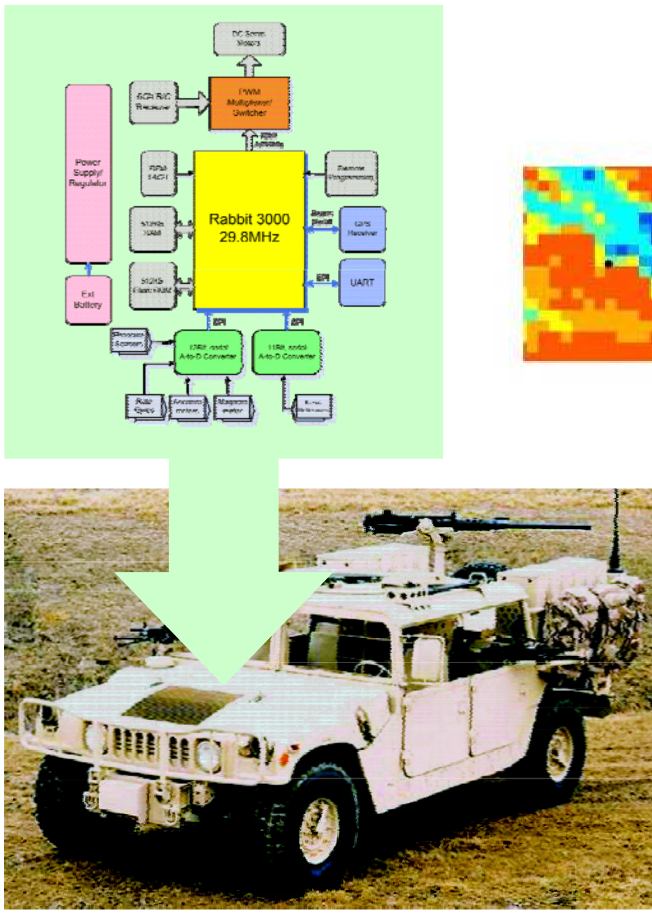


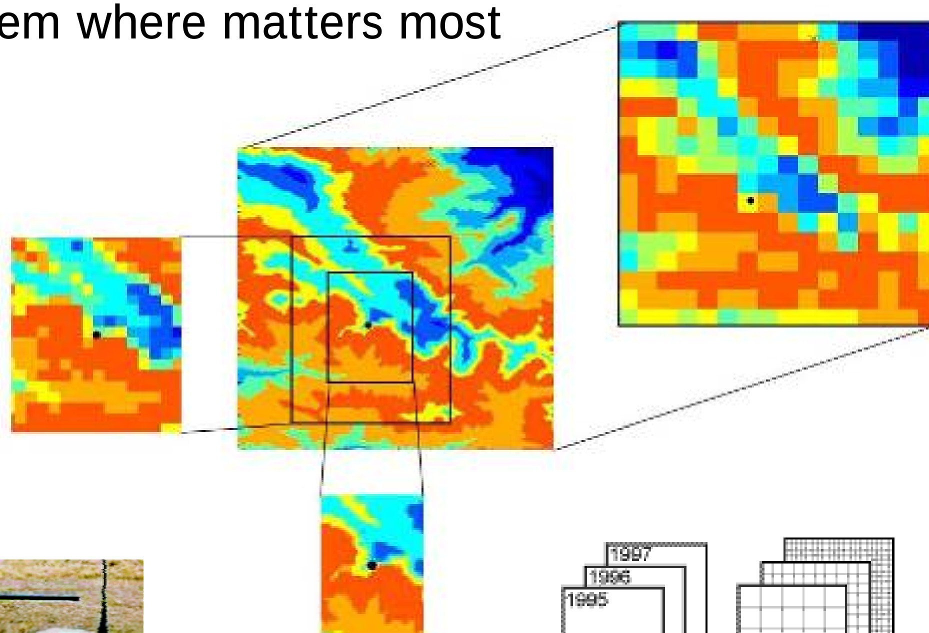
Trail Braking

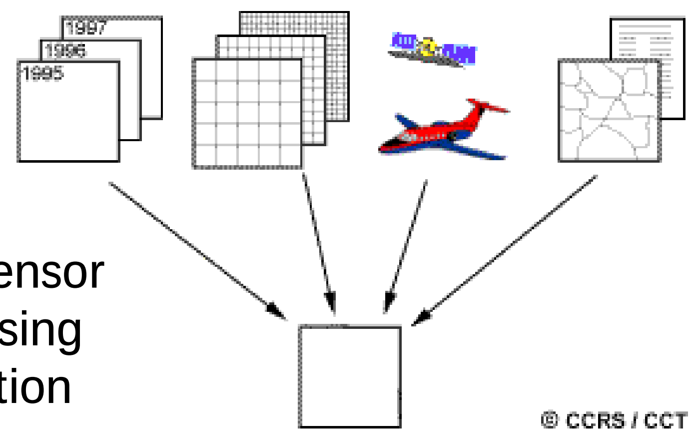
Multi-res Path Planning

Motivation: **-** Limited on-board comp resources

- Use them where matters most







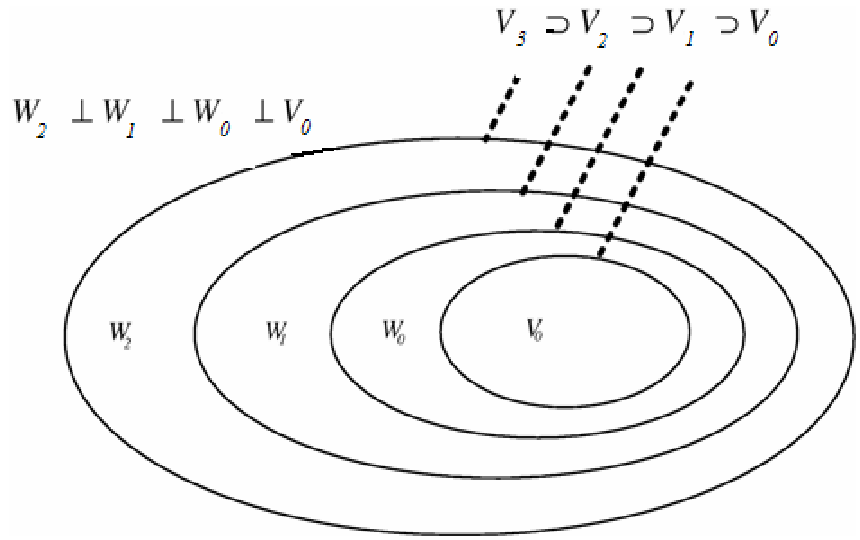
Multires/multisensor
data processing
and integration

Wavelet-Based Cell Decomposition

$$L^2(\mathbb{R}) = \mathcal{V}_0 \bigoplus_{j=0}^{+\infty} \mathcal{W}_j = \bigoplus_{j=-1}^{+\infty} \mathcal{W}_j = \lim_{j\to\infty} \mathcal{V}_j$$

$$\mathcal{V}_j = \mathrm{cl}(\mathrm{span}\{\sqrt{2^j}\phi(2^j x - k)\}$$

$$\mathcal{W}_j = \mathrm{cl}(\mathrm{span}\{\sqrt{2^j}\psi(2^j x - k)\}$$



$$\Phi_{j,k,\ell}(x,y) = \phi_{j,k}(x)\phi_{j,\ell}(y)$$
$$\Psi^1_{j,k,\ell}(x,y) = \phi_{j,k}(x)\psi_{j,\ell}(y)$$
$$\Psi^2_{j,k,\ell}(x,y) = \psi_{j,k}(x)\phi_{j,\ell}(y)$$
$$\Psi^3_{j,k,\ell}(x,y) = \psi_{j,k}(x)\psi_{j,\ell}(y)$$

$$\boxed{\text{DWT} \sim O(n)}$$

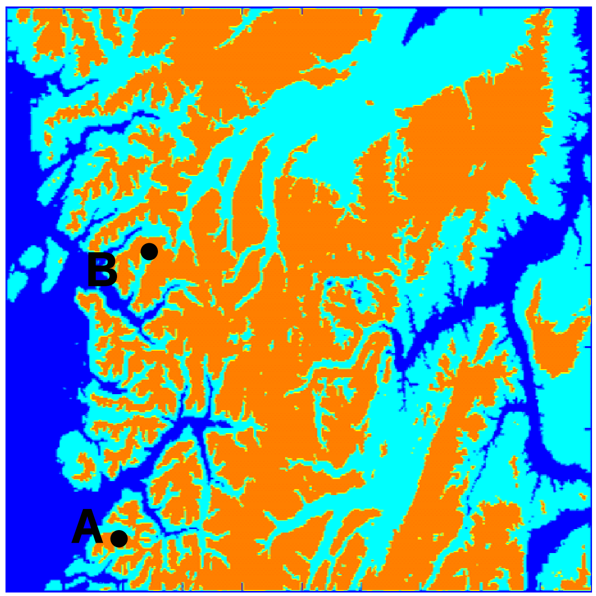
The wavelet decomposition

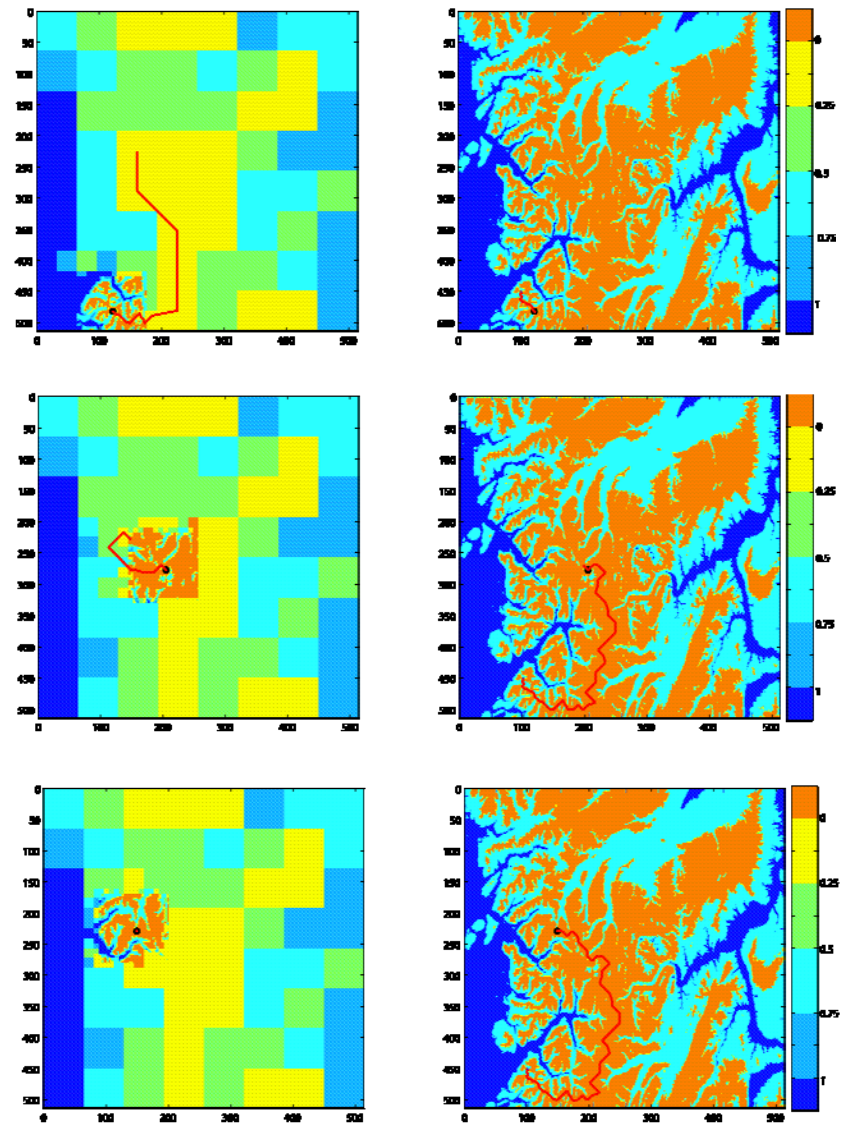
$$f(x,y) = \sum_{k,\ell=0}^{2^{J_{\min}}-1} a_{J_{\min},k,\ell}\,\Phi_{J_{\min},k,\ell}(x,y) + \sum_{i=1}^{3}\sum_{j=J_{\min}}^{J-1}\sum_{k,\ell=0}^{2^j-1} d^i_{j,k,\ell}\Psi^i_{j,k,\ell}(x,y)$$

induces a cell decomposition of $\mathcal{W}$

$$Cd = \Delta C_d^{J_{\min}} \oplus \Delta C_d^{J_{\min}} \oplus \cdots \oplus \Delta C_d^{J_{\max}-1}$$

Example





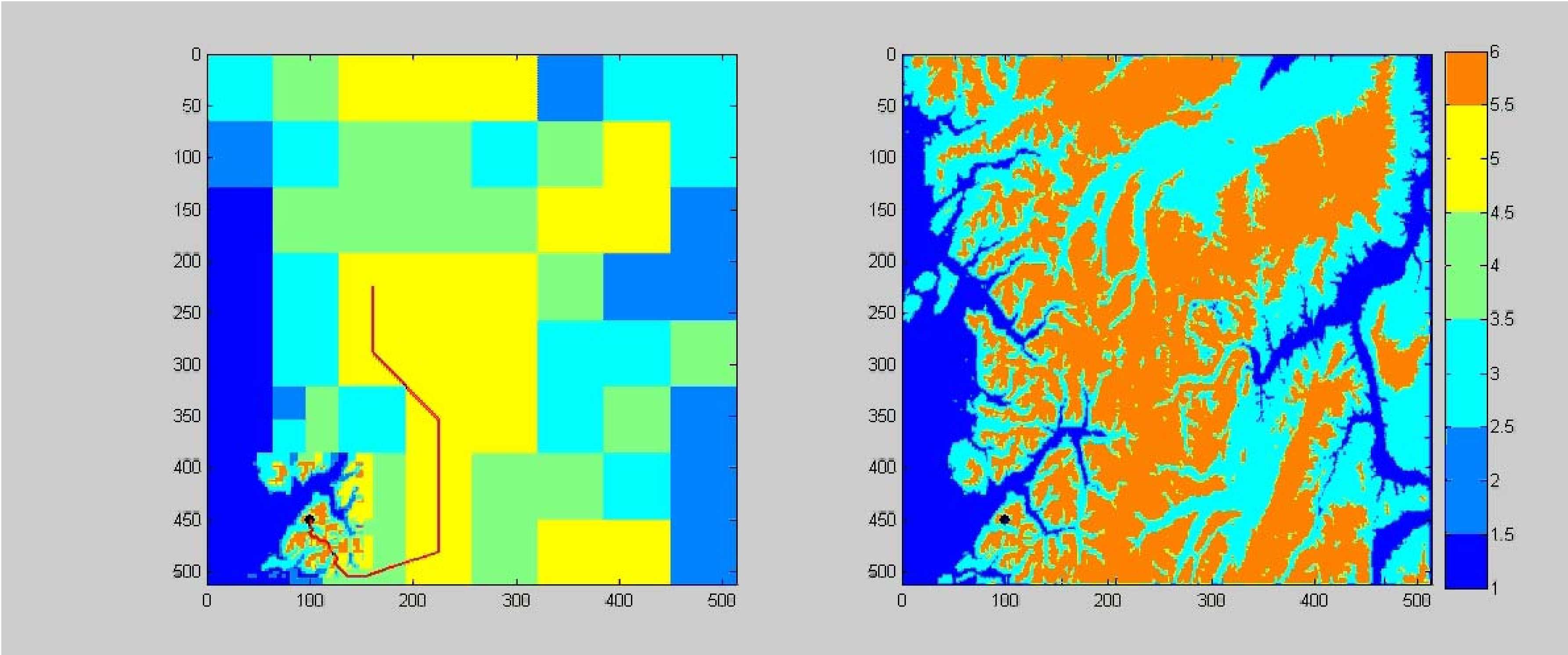
Real topographic data

Objective: Avoid blue areas

Original data 512x512

Planning over cells of 64 and 8 units

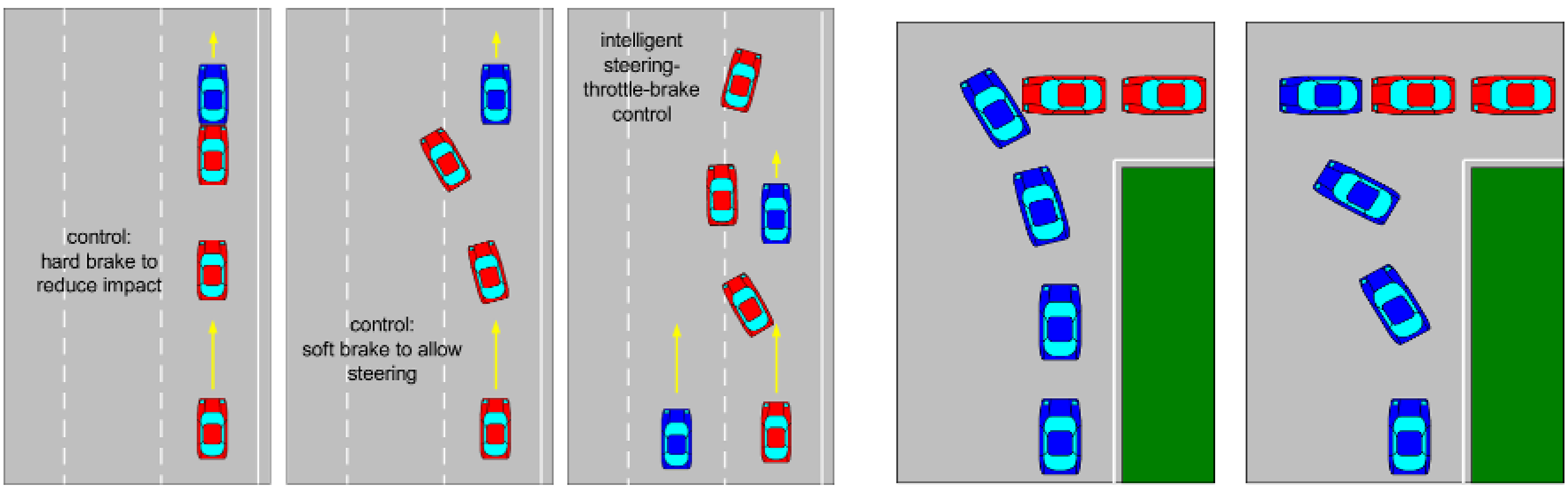
Animation



DCSL

Passenger Vehicle Active Control

- Expand operational regime of passenger vehicles
- Driver-assist, “drive by wire”
- Driver management systems
- Posture control



GPS for Navigation, Modeling, and Control of UGVs

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Director of Auburn University's

GPS and Vehicle Dynamics Lab (GAVLAB)

GPS/INS: The Perfect Complement

GPS (Low Frequency Sensor)	INS (High Frequency Sensor)
▪ Limited to 1-20 Hz ▪ Stable over long periods of time ▪ Stochastic zero mean noise ▪ Unbiased ▪ Noisy	▪ Higher output rates available ▪ Drift over long periods ▪ Noise due to vehicle dynamics ▪ Biased

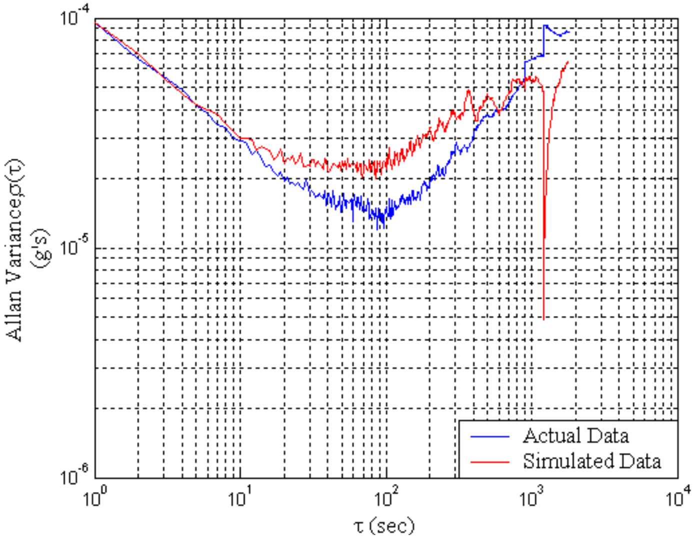
- The combination provides a high update rate, low noise, unbiased measurement solution
- Various Integration Techniques
  - Tightly Coupled (offers INS aiding with limited satellites, i.e. Urban Canyons)
  - Ultra-Tightly Coupled (offers improved noise immunity and instantaneous reacquisition after short outages, i.e. jamming or foliage environments)

IMU Modeling

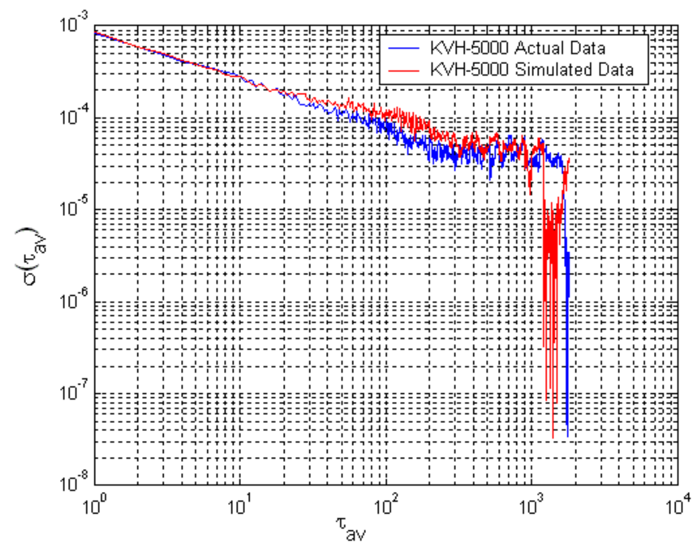
- Develop models to predict performance
- Model various grade (including MEMS based) inertial sensor characteristics
- Validate simulated data with experiments

$$\omega_{meas} = SF \cdot \omega_{act} + b_{const} + b_{walk} + \nu$$

Low Grade IMU



Mid-Grade IMU

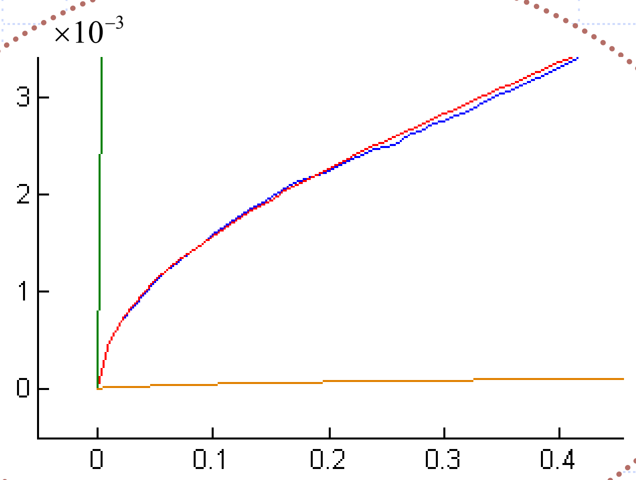


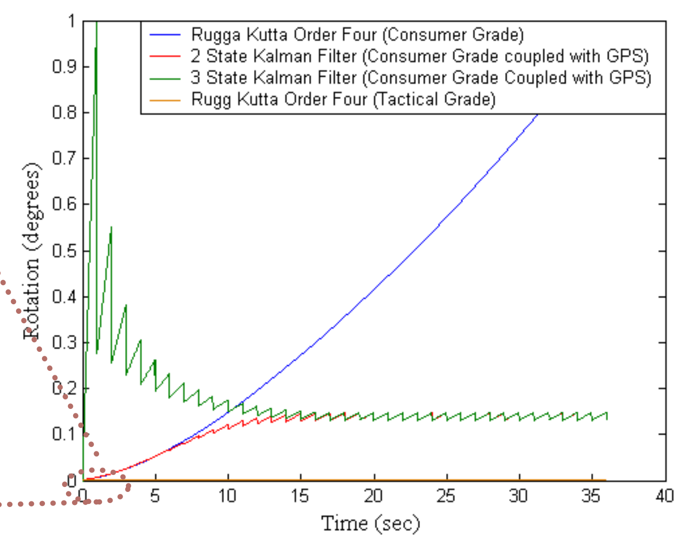
Gyroscope Comparison

- Blending GPS and consumer grade gyro bounds heading error
- Pure tactical grade gyro integration has less error

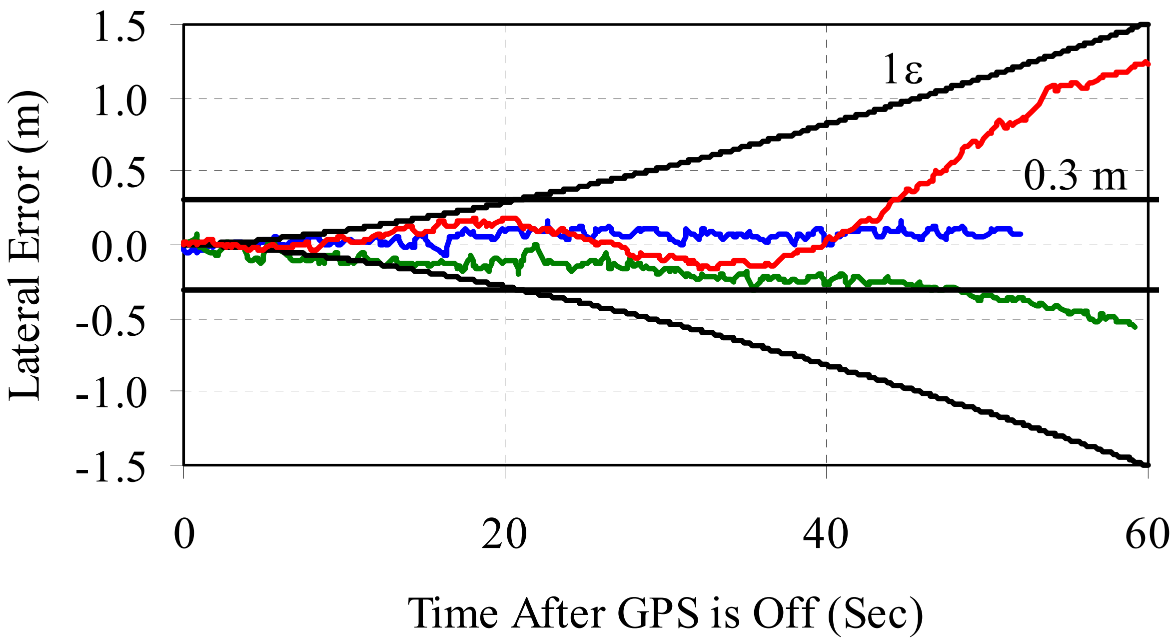
Classification Characteristics Used to Categorize Rate Gyros

Rate Gyro	Attribute	Units	Specification
Consumer			
	Random walk	°/sec/√Hz	0.05
	Bias Time Constant	sec	300
	Bias Variation	°/hr	360
Tactical			
	Random walk	°/sec/√Hz	0.0017
	Bias Time Constant	sec	100
	Bias Variation	°/hr	0.35





Lateral Errors When Dead Reckoning (No GPS)



3 Tests

- V_X=2 m/s
- Line Tracking

Results

- Errors < 0.3m for 40 sec
- Errors < ε_y

Error Analysis:

$$\dot{y}_E = V_X \psi_E = V_X \sigma_{\dot{\psi}} \sqrt{T_S t} \qquad \varepsilon_y(t) = \tfrac{2}{3} V_X \sigma_{\dot{\psi}} \sqrt{T_S} * t^{\frac{3}{2}}$$

INS Aiding Using External Aids

- Laser scanners provide environment information which can be used to navigate in a defined corridor
- Provides ability to estimate the following:
  - Velocity, local heading
  - Local lateral error (for use in some controllers)
  - Lateral vehicle movement (also makes vehicle sideslip and/or lateral velocity observable)
- Currently using well defined aids to define corridor
  - Walls, lane markings, etc.
- Preliminary experiments run in hallway and on test track

Unstructured Object Registration

- How to do object registration/aiding in unstructured and dynamic environments
  - Use trees, road edge, etc to define corridor and aid INS

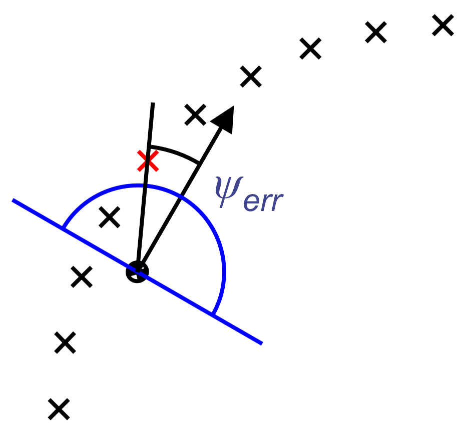
  

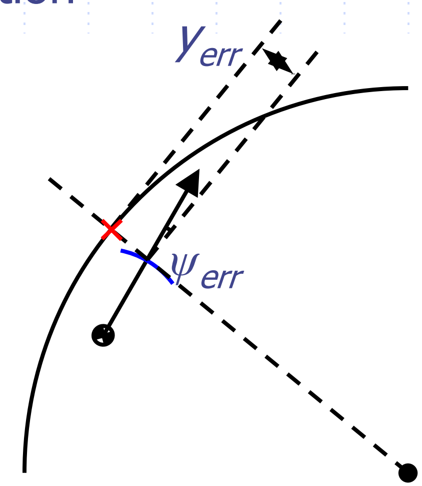
Images from UGV Test Course at Auburn

Steering Control Strategies

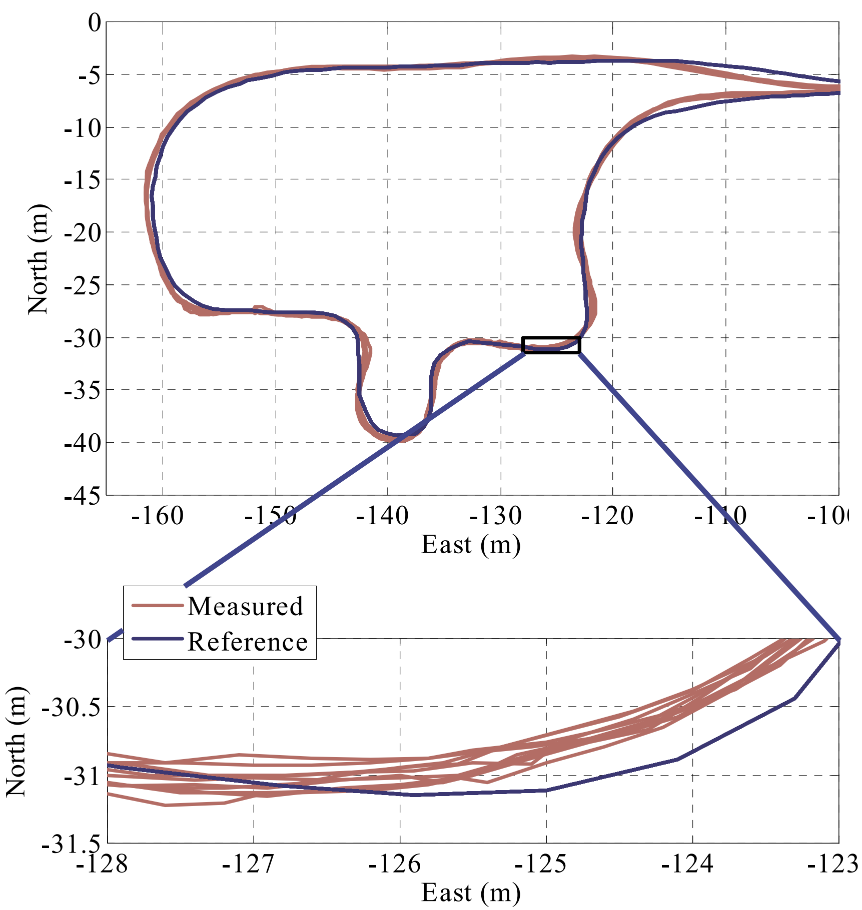
- Waypoint
  - Easier to implement and tune (by hand)
  - Requires fewer model parameters
- Driving to waypoints is not best control method
- Results in decreased tracking accuracy
  - Vehicle oscillates more

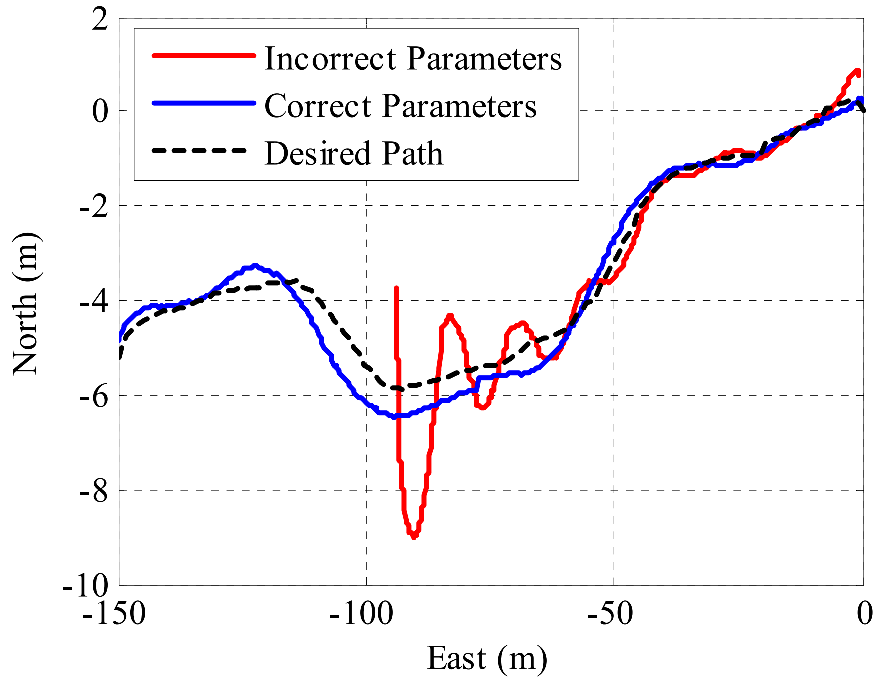
- Line Tracking
  - Need good model
  - Requires more parameters/states
  - Harder to define error
  - Provides improved tracking
- Two errors are important
  - Heading
  - Lateral position





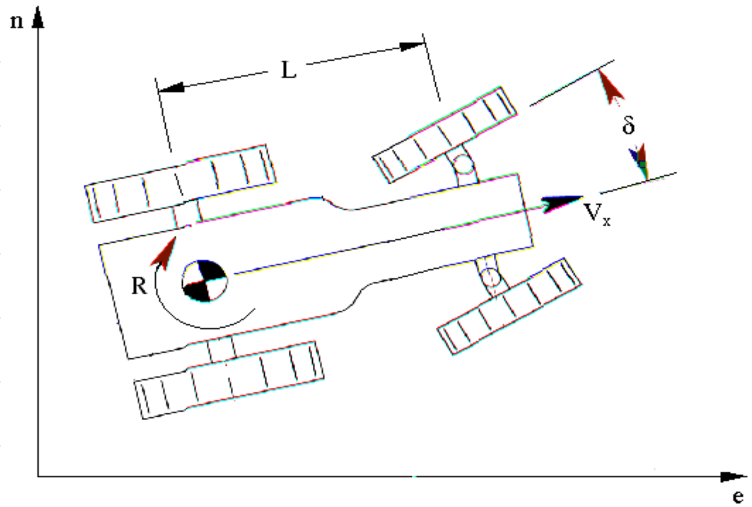
ATV Way-Point Controller Performance





Need good model during aggressive maneuvers

Various Yaw Dynamic Models



Bicycle Model

$$\frac{R(s)}{\delta(s)}=\frac{a\,C_{\alpha f}s+\dfrac{a\,C_{\alpha f}-c_1C_{\alpha f}}{mV}}{I_Z s^2+\dfrac{c_0I_Z+mc_2}{mV}s+\left(\dfrac{c_0c_2-c_1mV^2-c_1^2}{mV^2}\right)}$$

DC Gain: $R_{ss}=\dfrac{V_x}{L+K_{US}V_x^{\,2}}\delta$

Neutral Steer Model (K_{us}=0)

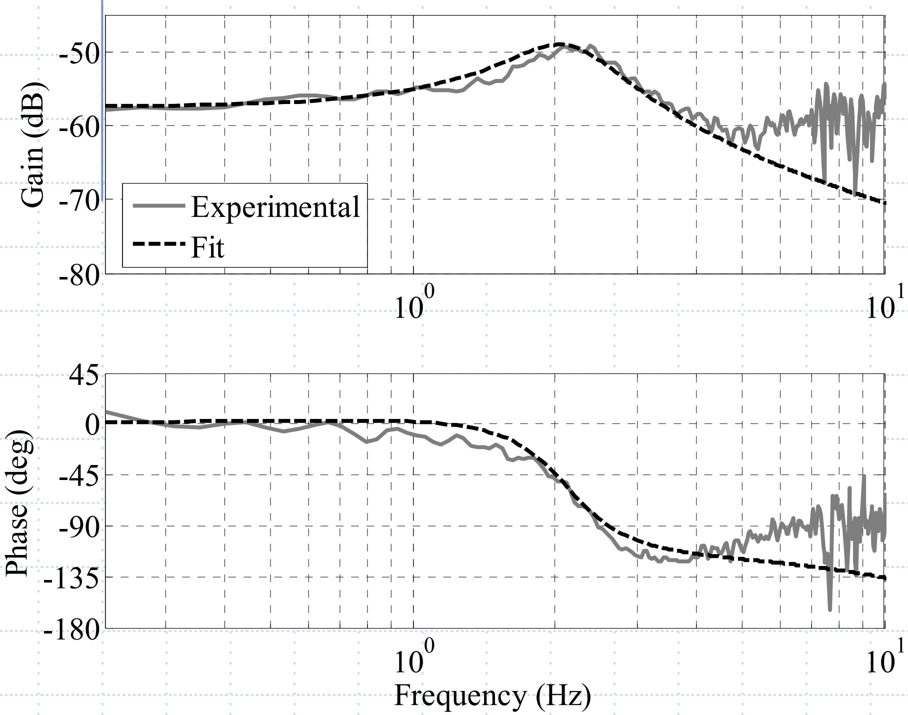
$$\frac{R(s)}{\delta(s)}=\frac{a\,C_{\alpha f}}{I_Z s+\dfrac{c_2}{V}}$$

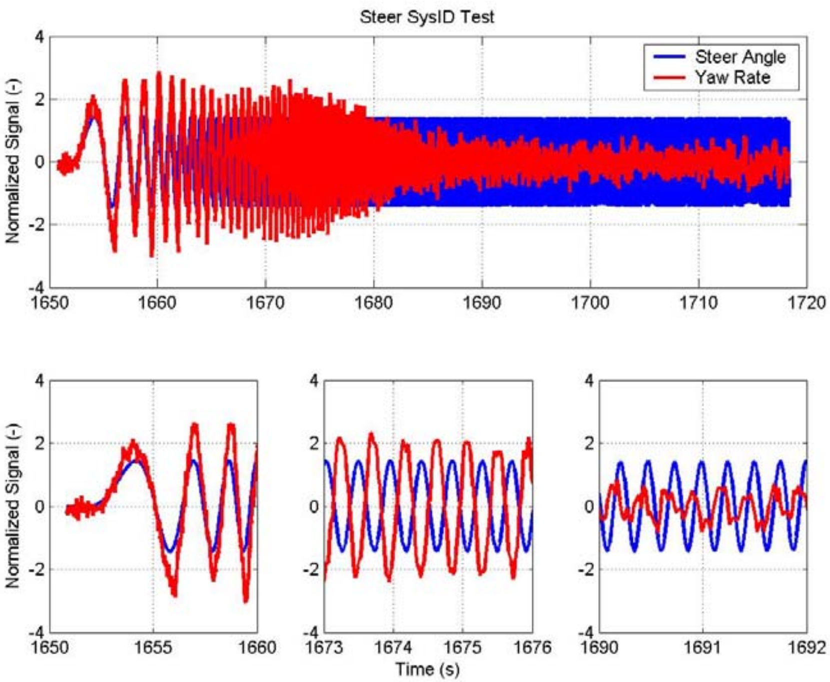
Kinematic Model

$$R=\frac{V_x}{L}\delta$$

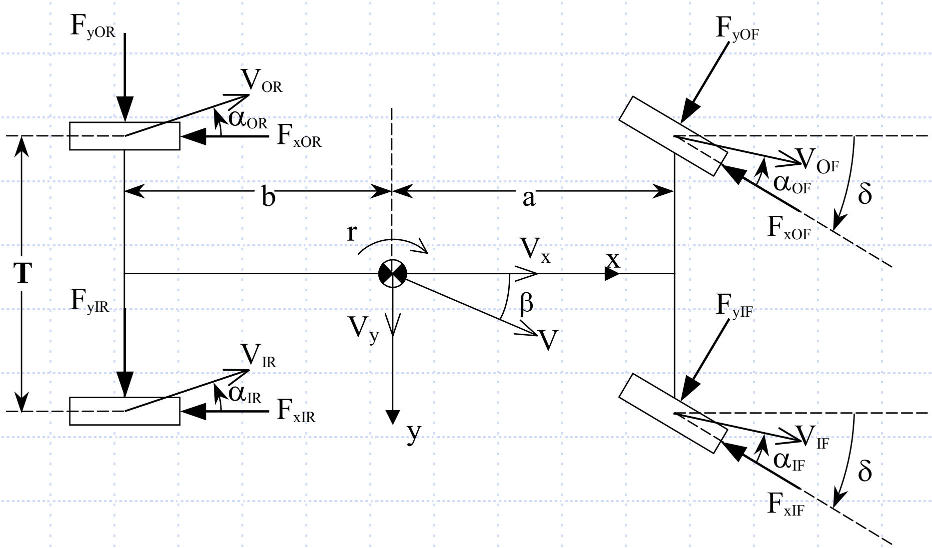
Identification of ATV Dynamics

$$\frac{r}{\delta} = \frac{k_v\left(s+n_v\right)}{s^2+2\zeta_v\omega_v s+\omega_v^2}$$





Typical Yaw Vehicle Model



V = velocity

r = yaw rate

ψ = vehicle heading

δ = steer angle

β = body side slip

α = tire side slip

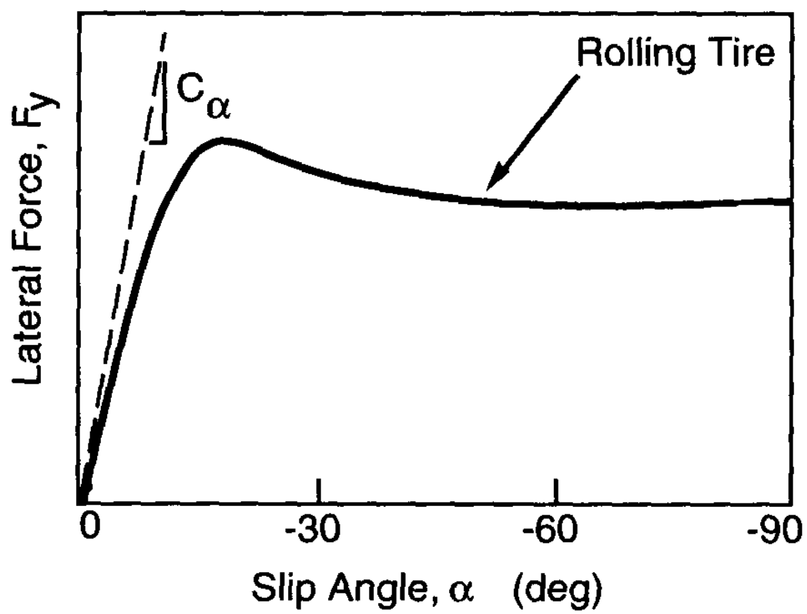
C_α = cornering stiffness

$$F_y = C_\alpha \alpha$$

$$\begin{bmatrix} \dot{\beta} \\ \dot{r} \end{bmatrix} = \begin{bmatrix} \dfrac{-C_0}{mV} & -\left(1 + \dfrac{C_1}{mV^2}\right) \\ \dfrac{-C_1}{I_Z} & \dfrac{-C_2}{I_Z V} \end{bmatrix} \begin{bmatrix} \beta \\ r \end{bmatrix} + \begin{bmatrix} \dfrac{C_{\alpha f}}{mV} \\ \dfrac{aC_{\alpha f}}{I_Z} \end{bmatrix} \delta$$

Tire Behavior

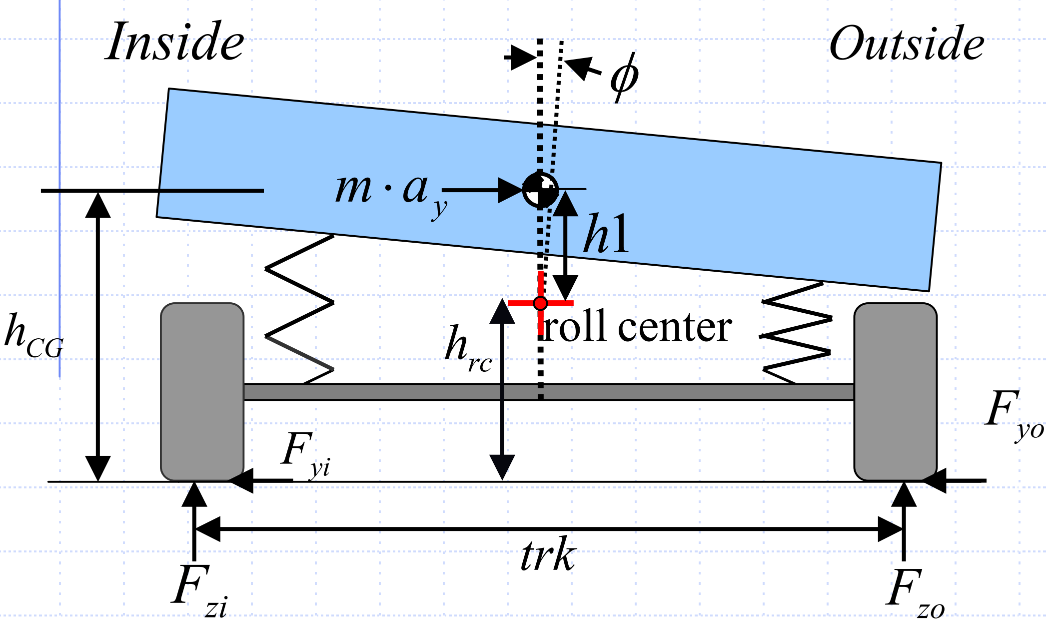
$$F_x = C_s \cdot s$$
$$F_y = C_\alpha \cdot \alpha$$



- Linear for small slip angles
- Saturates at higher slip angles (vehicle slides)
- Varies with loading
- Corning stiffness depends on tire only
- Peak force changes with surface (μ) and tire

Pacejka "Magic" Tire Model (SAE Paper 870421)

Roll Modeling (for anti-roll)



Developed simple vehicle models to study effect of various properties on handling and roll dynamics

$$\text{Roll Rate} = \frac{W_t \cdot h1}{k_{\phi f} + k_{\phi r} - W_t \cdot h1}$$

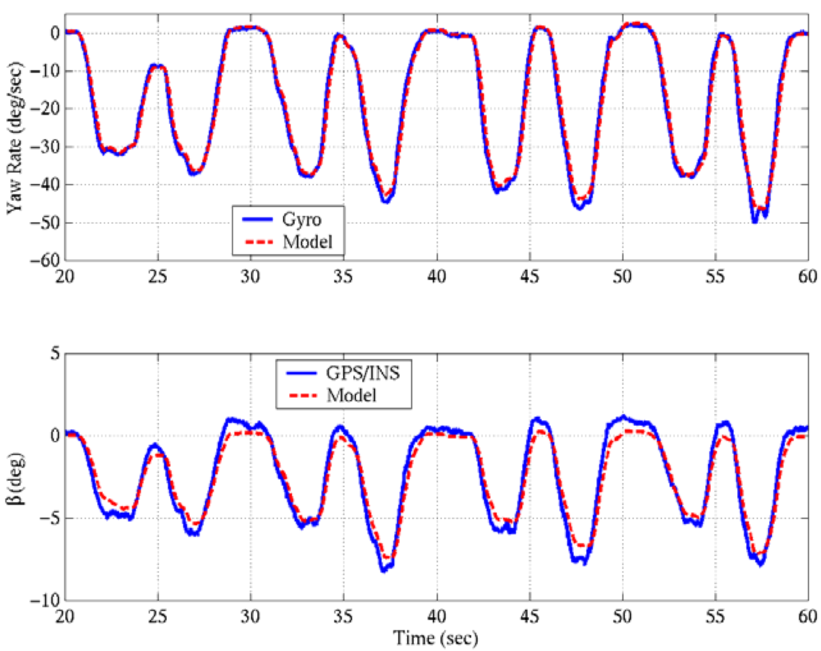
$$\phi_{ss} = \text{Roll Rate} \cdot a_y \qquad k_{\phi} = \text{roll stiffness}$$

$$\Delta F_z = f(\phi, a_y) \qquad \mathrm{a}_{\mathrm{y}} = \text{lateral accerlation}$$

Vehicle Model Validation

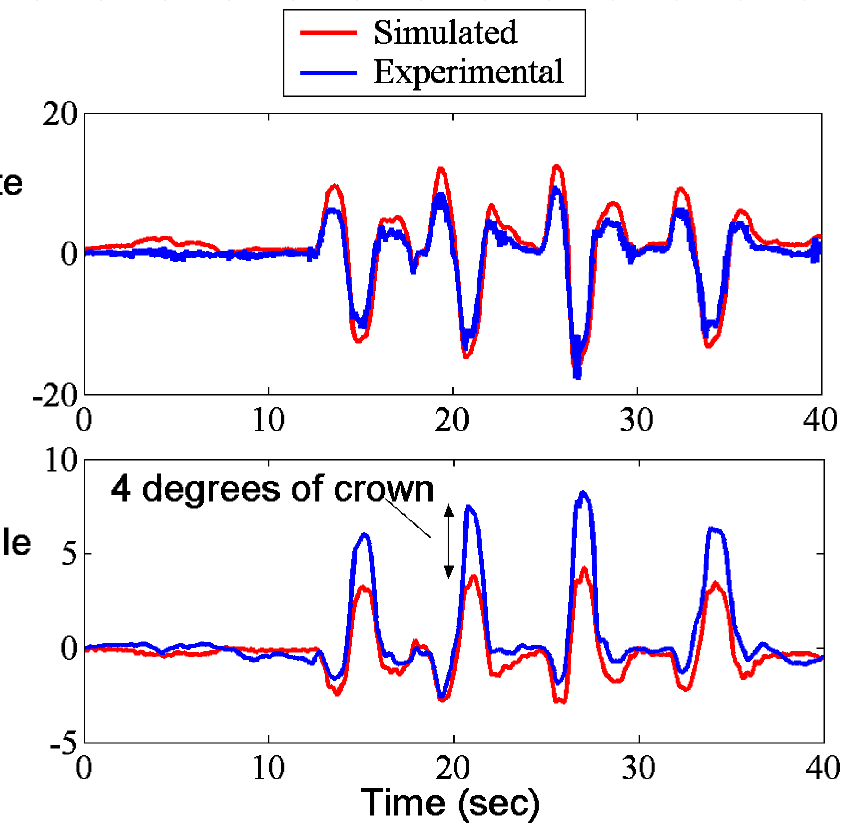
Crown of track visible
In roll measurement

Model Matches Actual

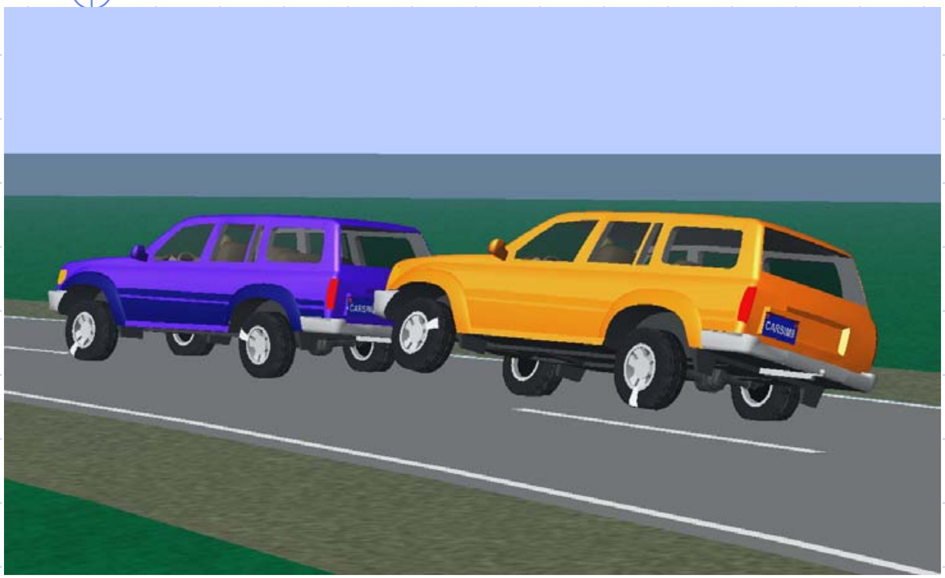


Yaw Rate (deg/s)

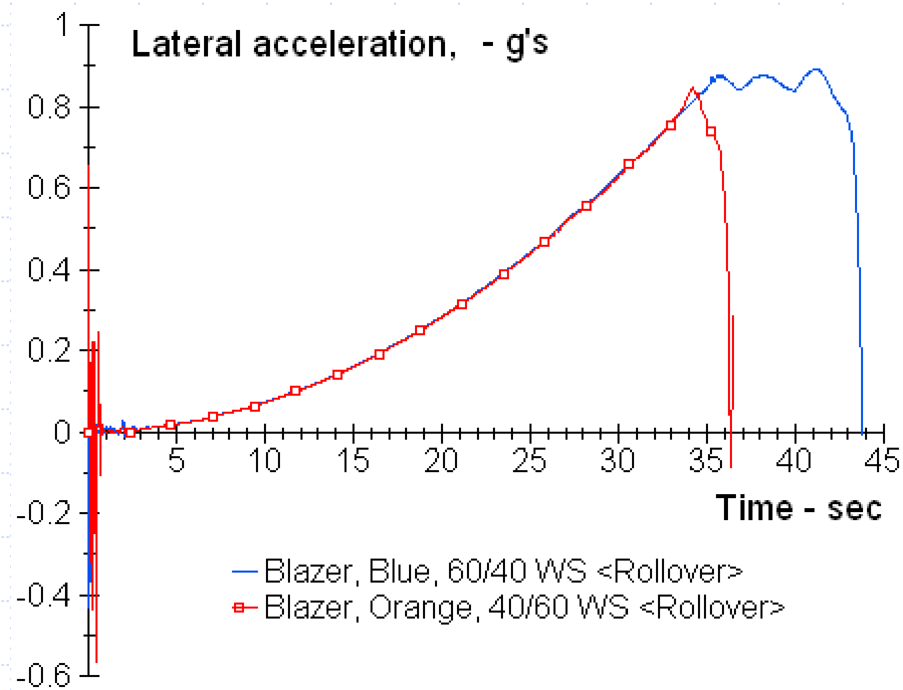
Roll Angle (deg)



Vehicle Rollover Simulations

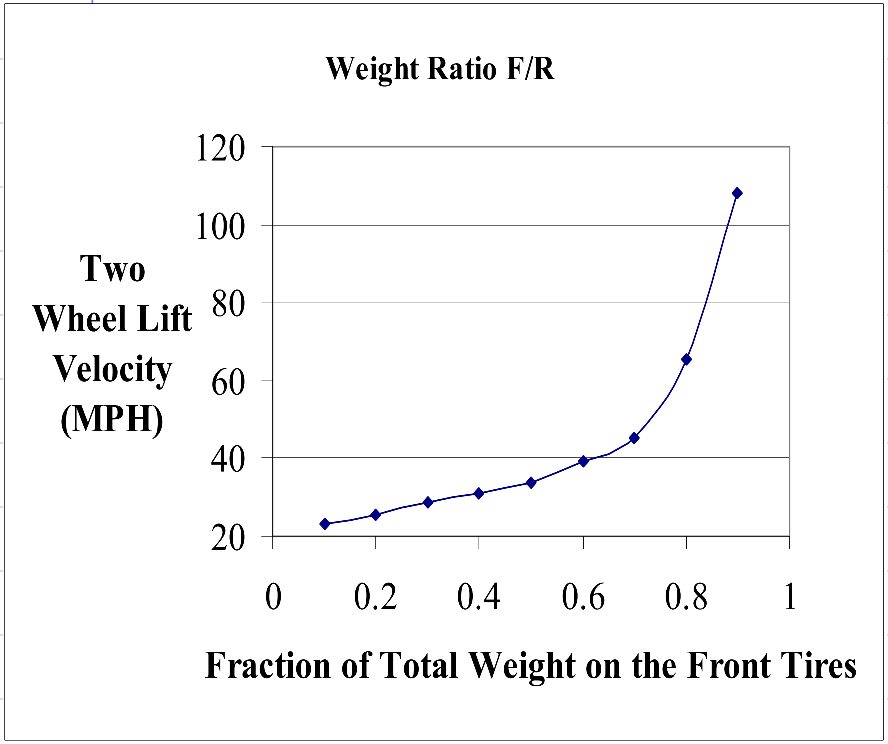


- Constant Radius - Steady acceleration maneuver
- Studies the effect of weight split on vehicle stability

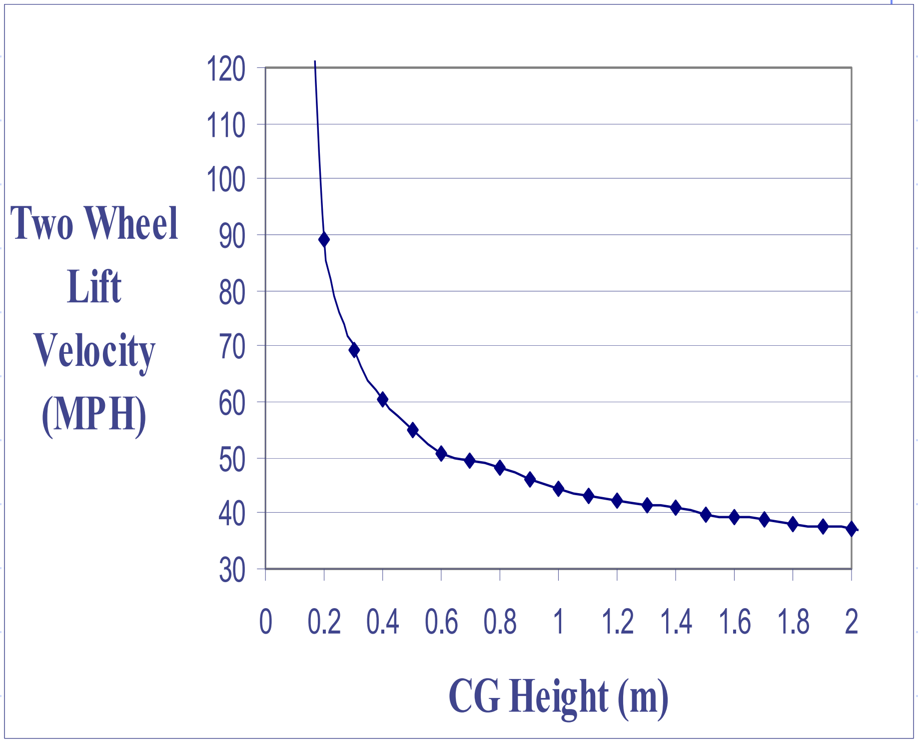


Effect of CG Location on Roll

Maneuver: Fishhook 1a
Varying CG Longitudinal Location



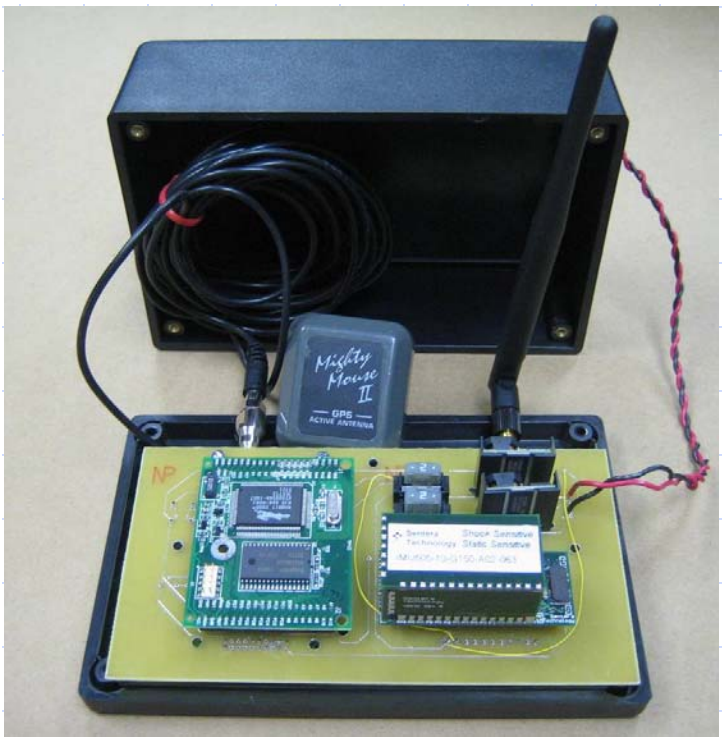
Constant SSF



Varying SSF

Small Low-Cost Vehicle GPS/INS System

- ESC Scaled Experiment Testbed



- CG Relocator
- GAVLAB GPS/INS System
  - IMU at 60 Hz
  - GPS at 4 Hz
  - Wireless Data Acquisition
  - Prototype Cost < $500

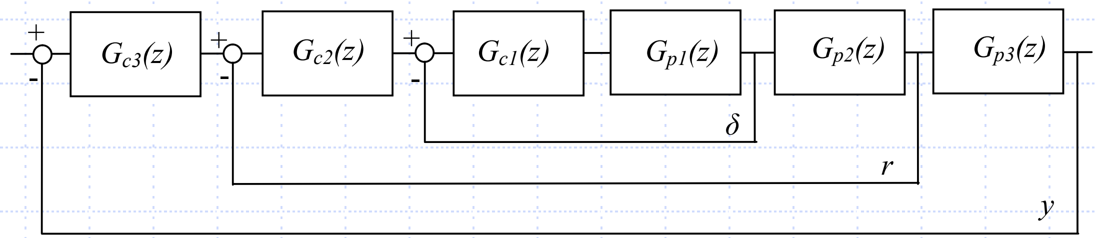
Rollover Mitigation (Using GAVLAB GPS/INS System)

Without ESC II **With ESC II**

Total System Dynamics (for Yaw Control)

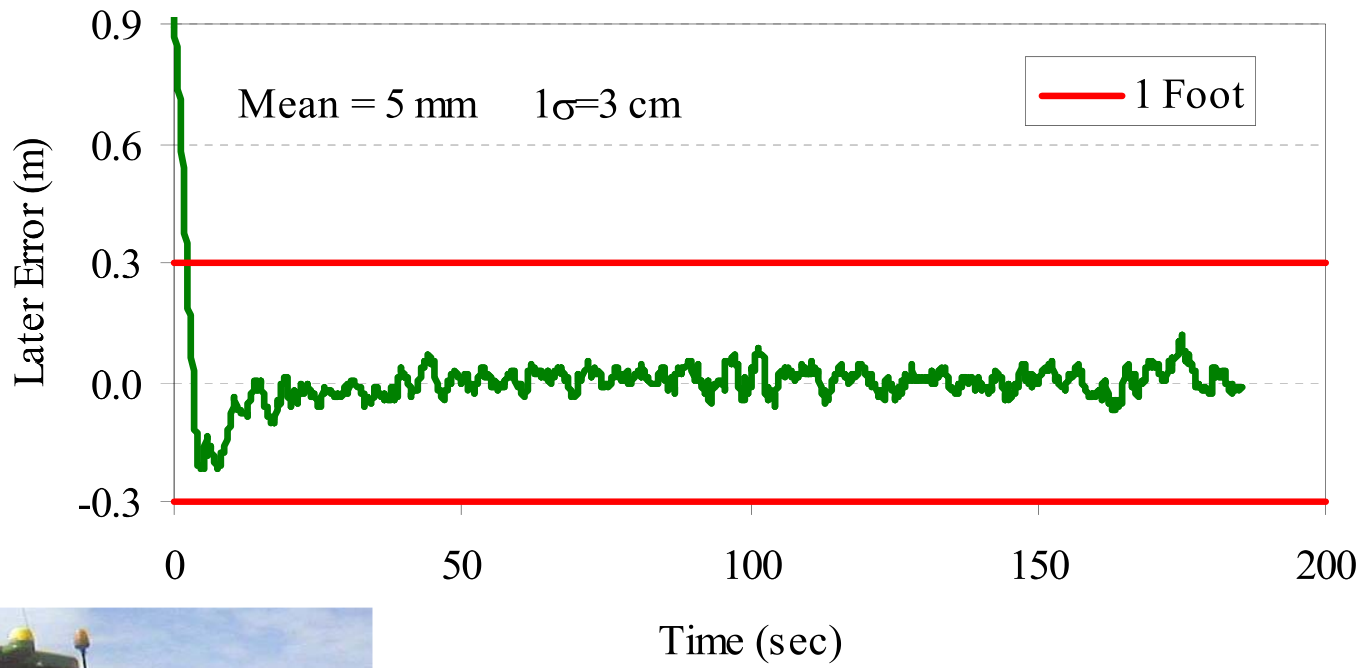
- Steering $$\frac{\delta}{u} = \frac{K_\delta}{\tau_\delta s + 1} \qquad \left(\dot{\delta} = u\right)$$
  - 1st order
    - Neglecting motor dynamics
- Vehicle $$\frac{r}{\delta} = \frac{k_v \left(s + n_v\right)}{s^2 + 2\zeta_v \omega_v s + \omega_v^2}$$
  - 2nd Order
- Error
  - Heading (1st order) $\dot{\psi} = r$
  - Lateral Position (2nd Order) $\dot{y} \approx V_X \psi$

Steering Control Strategies



- Classical
  - Cascaded
    - Design (need good model)
    - Hand-Tuning
- State Feedback
  - Need Good Model for Design
  - Need Estimator (also requires good model)

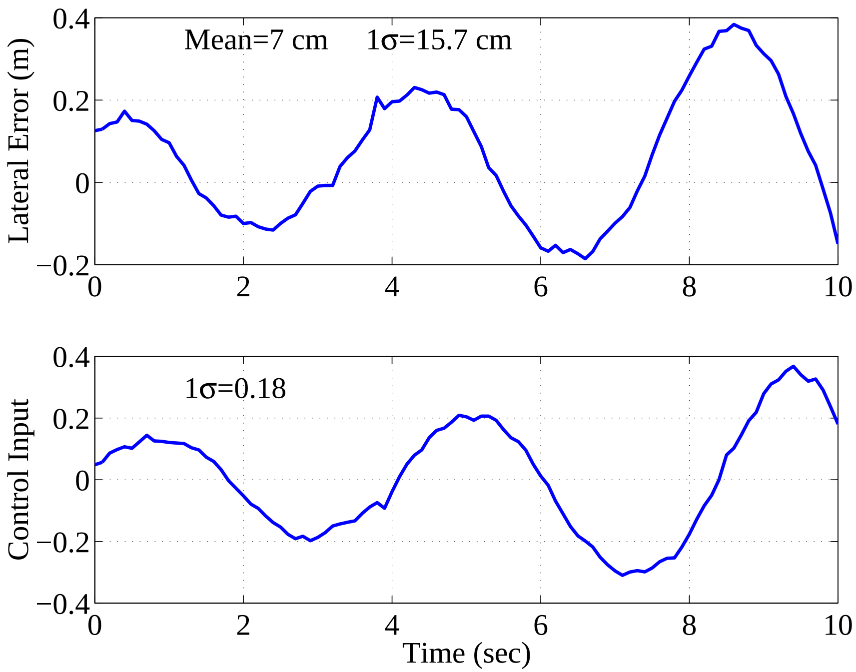
Off Road Line Tracking Control

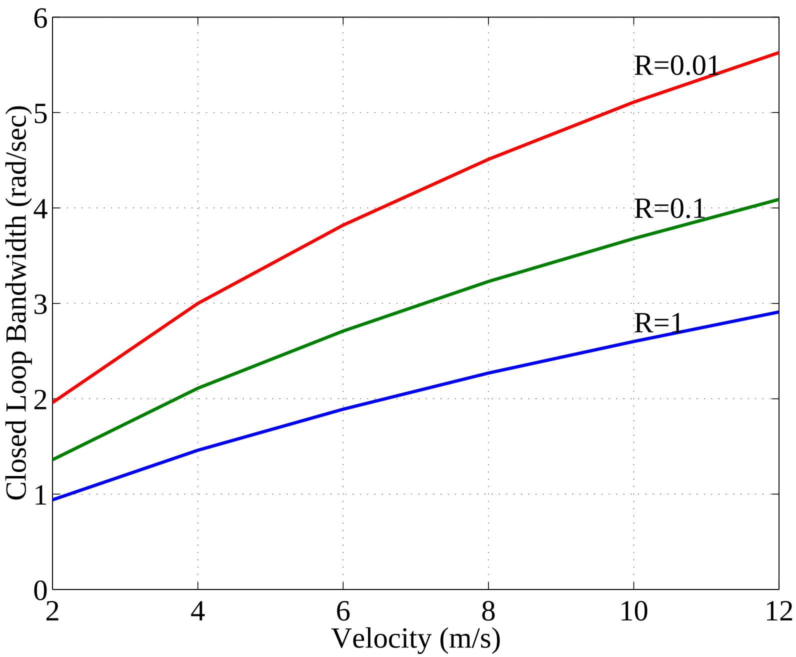


Effect of Velocity on LQR Closed Loop Bandwidth

$$u = -K_{comp} X_{comp}$$

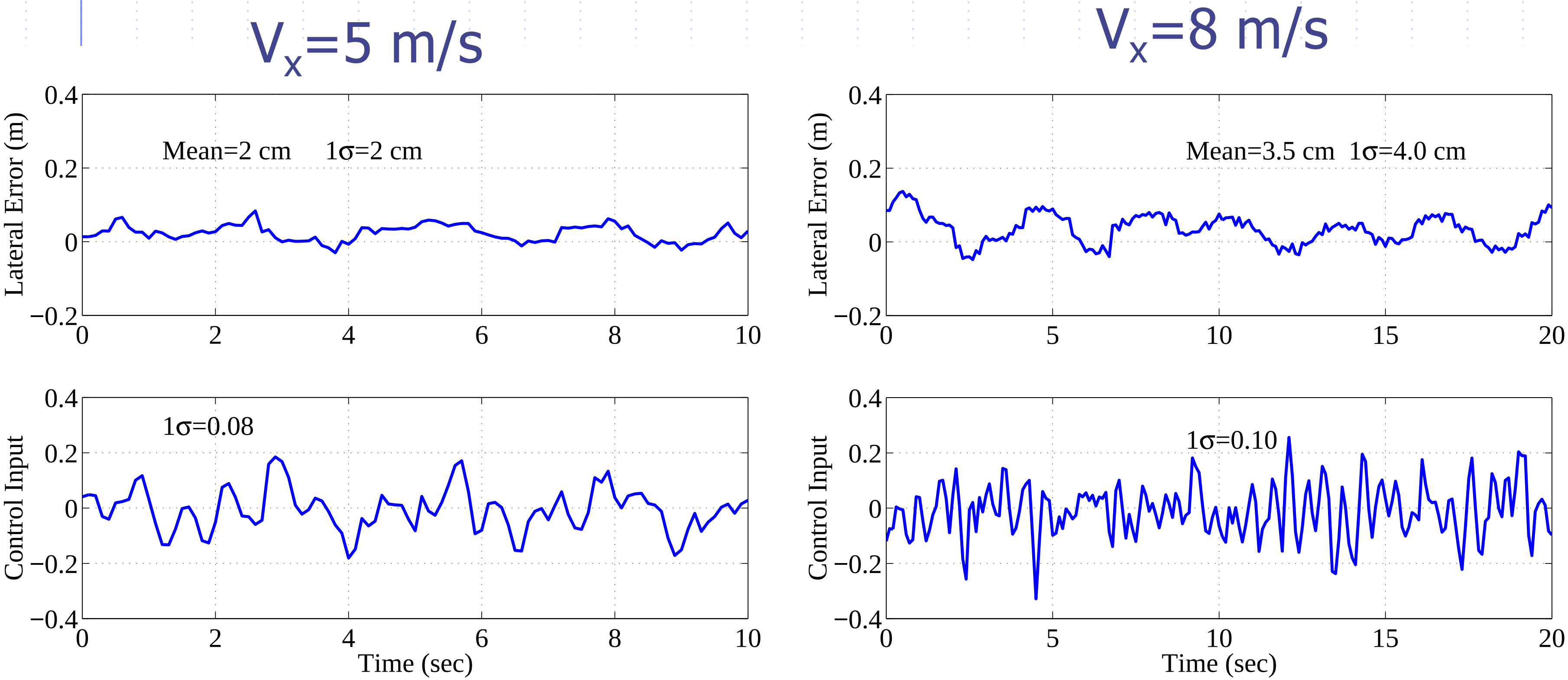
- Closed loop bandwidth increases with velocity for a given set of LQR control weights
- Closed loop bandwidth approaches 2nd order tractor bandwidth dynamics at higher speeds





High Speed Control

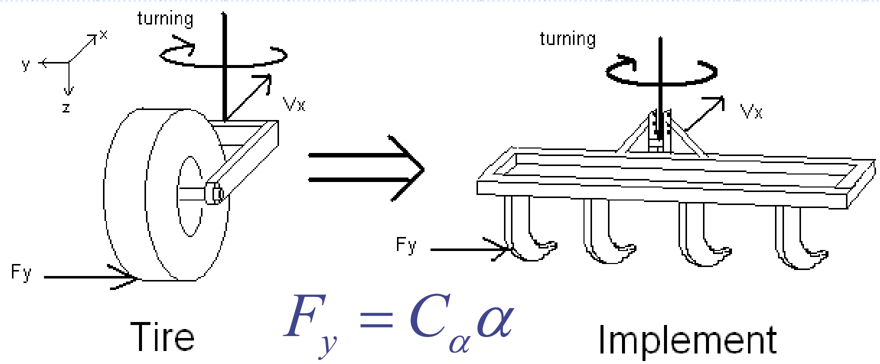
- Accurate control at full range of tractor speeds (using correct vehicle dynamics)



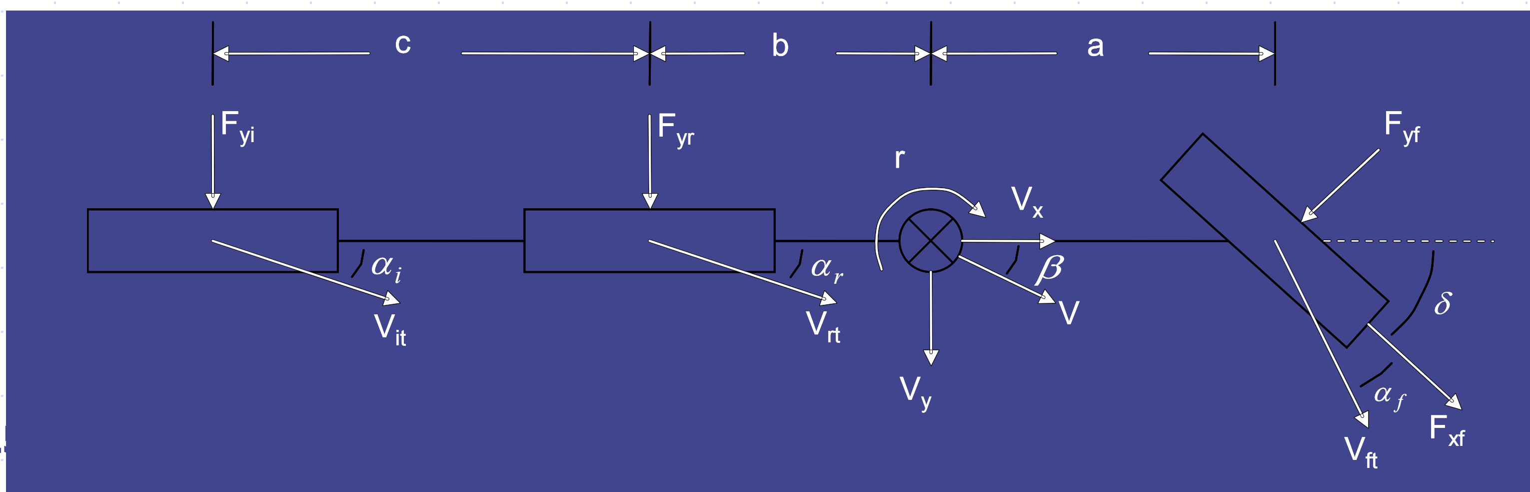
Additional Loads

- Can a model capture the behaviors actually seen from real data?
- Models useful to steering control describe the turning rate of the tractor from a given steering angle

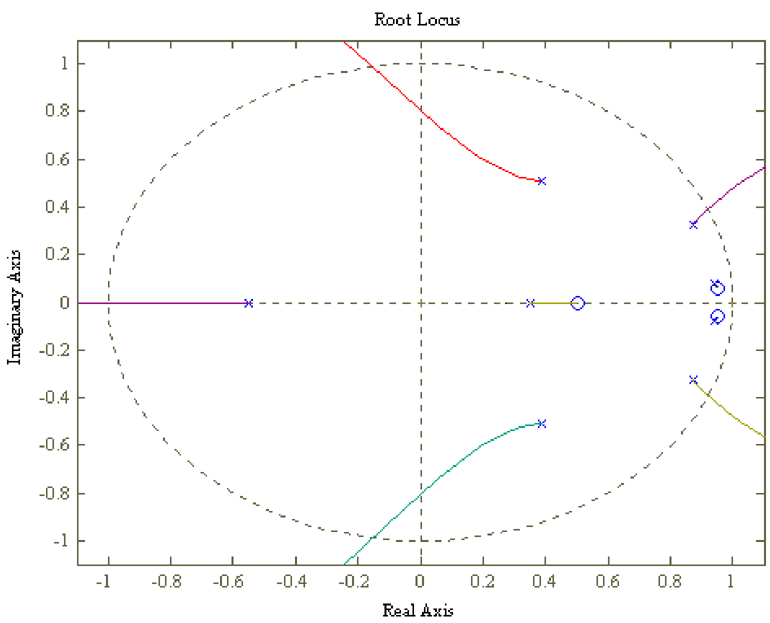
Implement described using a tire model



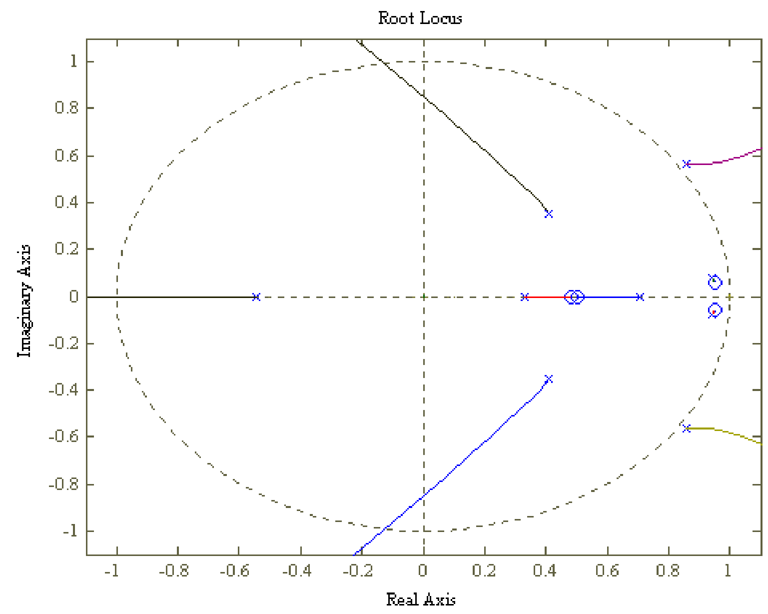
$$F_y = C_\alpha \alpha$$



Effect of Hitched Implement Dynamics

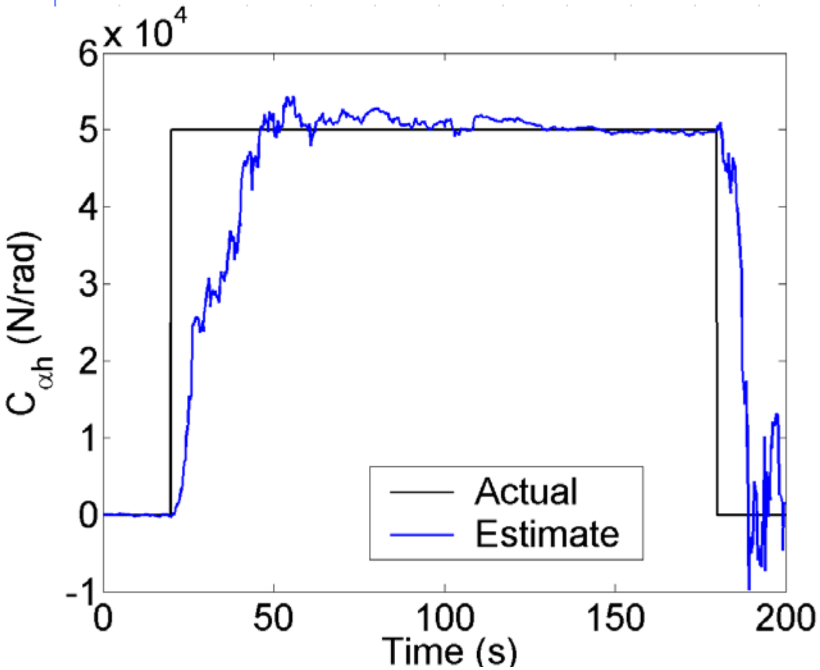


With Correct Implement Model

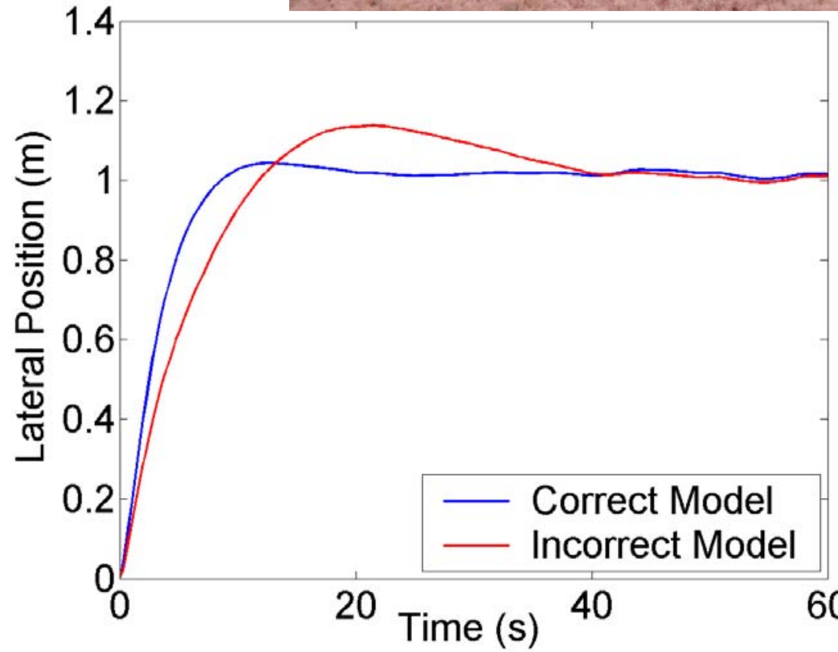


Neglecting Implement Dynamics

EKF Hitch Estimation



Estimation of Hitch Cornering Stiffness from Implement

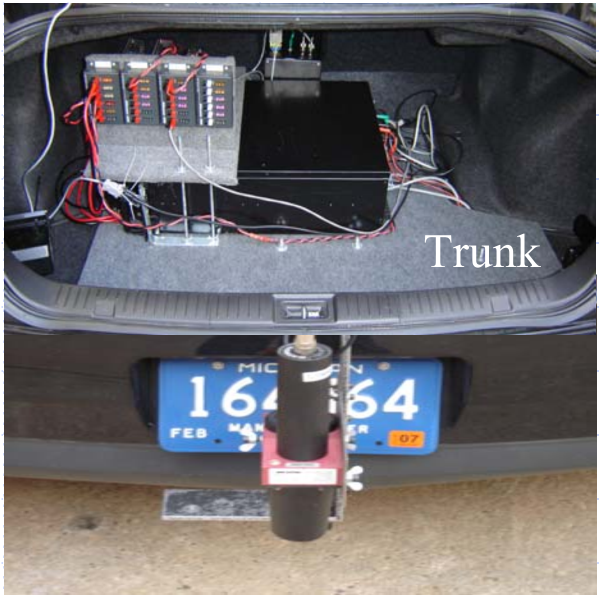


Control with Correct and Incorrect Implement Model

Instrumented Test-Vehicle Used for Parameter Estimation

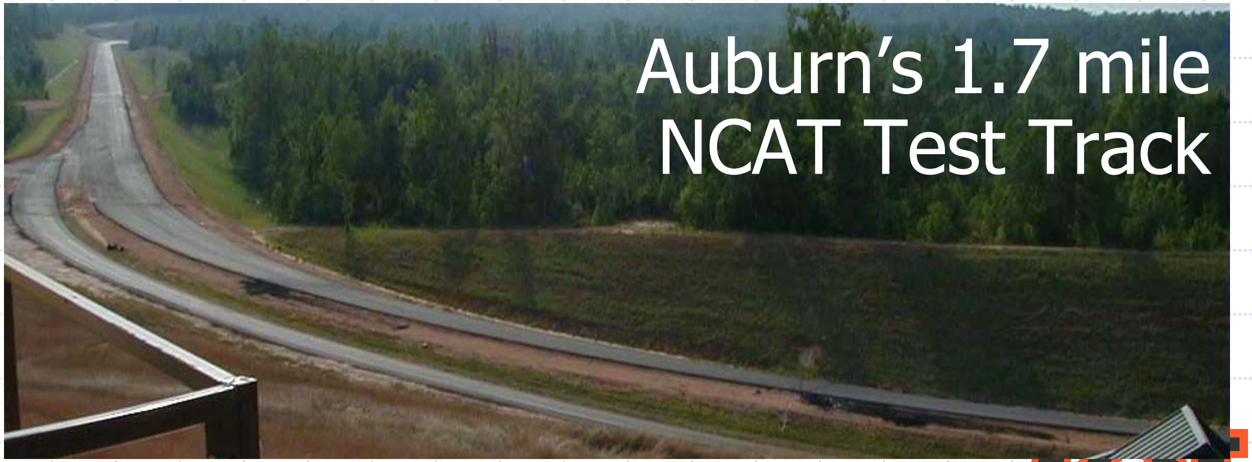
- CrossBow IMU
  - 3 Axis Acceleration
  - 3 Axis Rotation Rate
- DATRON Velocity
  - Longitudinal Speed
  - Lateral Speed
- CAN
  - Wheel Speeds
  - Steer Angle
- Starfire/Beeline GPS
  - Position & Velocity
  - Course
  - Heading & Roll
- On Board PC
  - Data Logging
  - Real Time Analysis


Center Console


Trunk

Dash

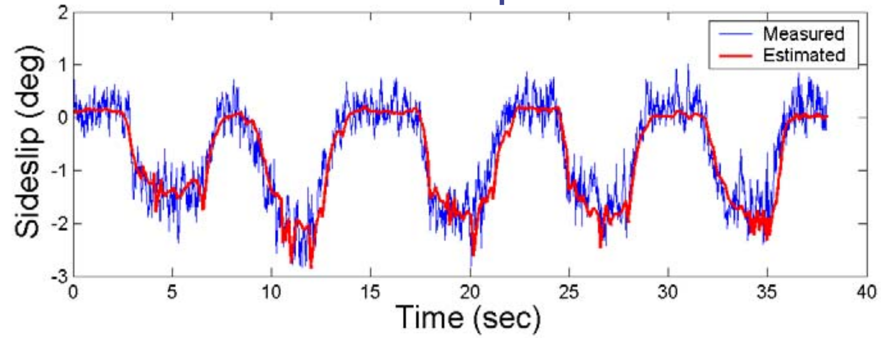

Experiment Site and Tests

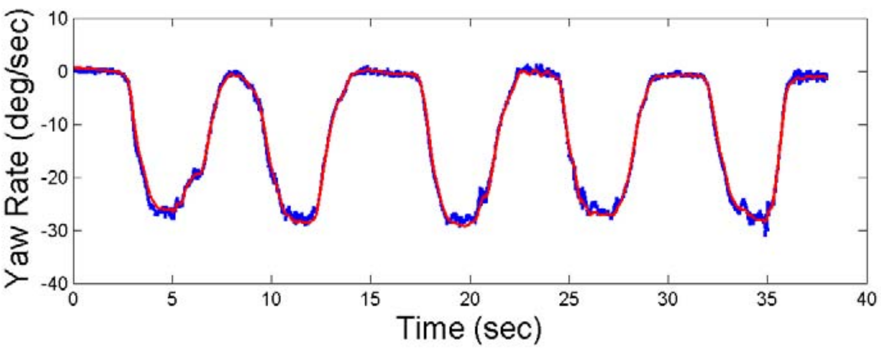


Vehicle State and Parameter Estimation

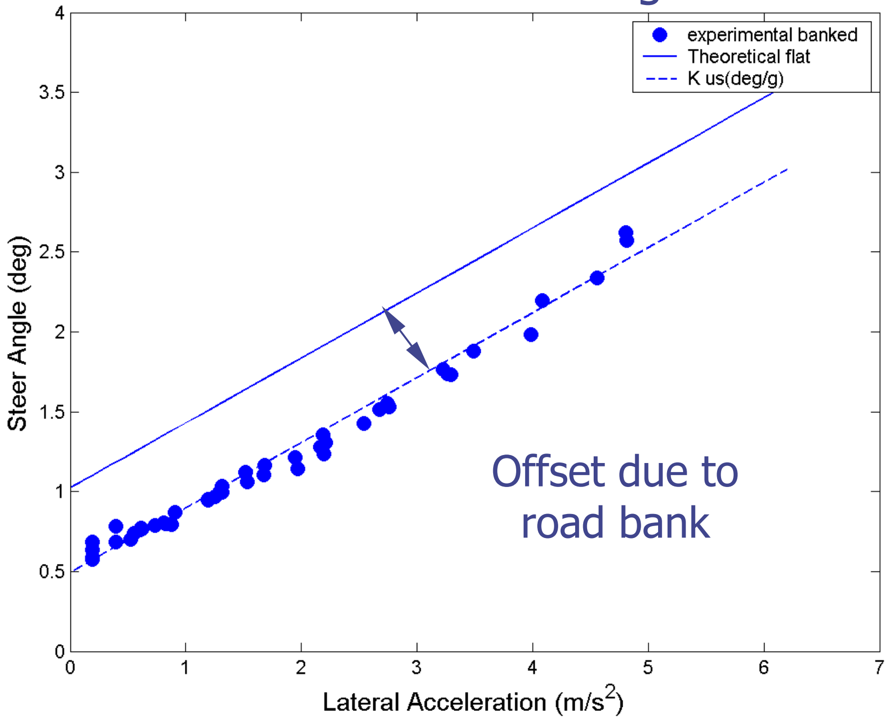
- Estimate vehicle parameters and states that may otherwise:
  - be difficult to measure
  - require expensive sensors
- Uses GPS and low cost inertial sensors with a vehicle test-bed

Estimation of Sideslip and Yaw Rate



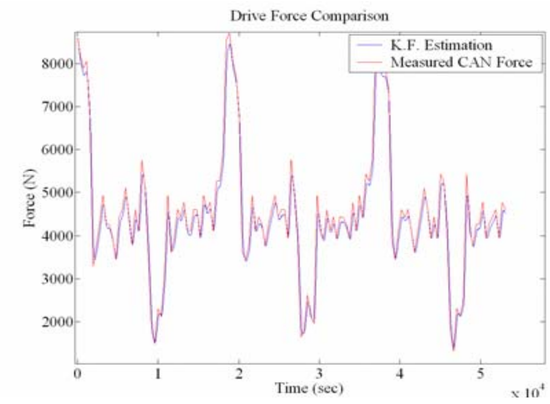


Estimation of Understeer gradient



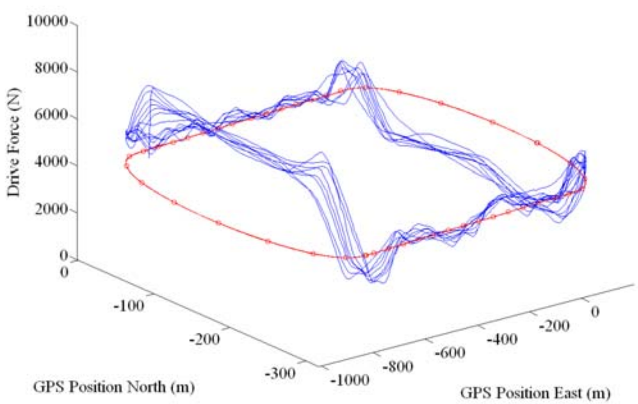
Force and Mass Estimation

- Use vehicle measurements to estimate:
  - Drive Force
  - Vehicle Mass
  - Air Drag
  - Rolling Resistance



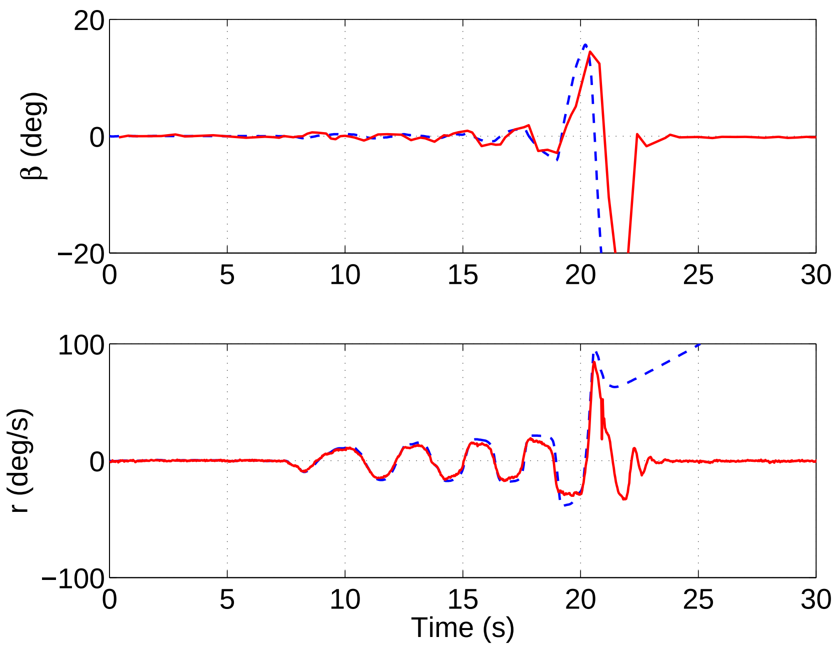
$$F_{engine} = \frac{\tau_{engine} N_{transmission} N_{final\ drive} \varepsilon_{mechanical}}{R_{tire}}$$

$$F_{drive} = \begin{bmatrix} \ddot{x} & V^2 & 1 \end{bmatrix} \begin{bmatrix} \hat{m} \\ \hat{C}_{df} \\ \hat{F}_{rr} \end{bmatrix}$$

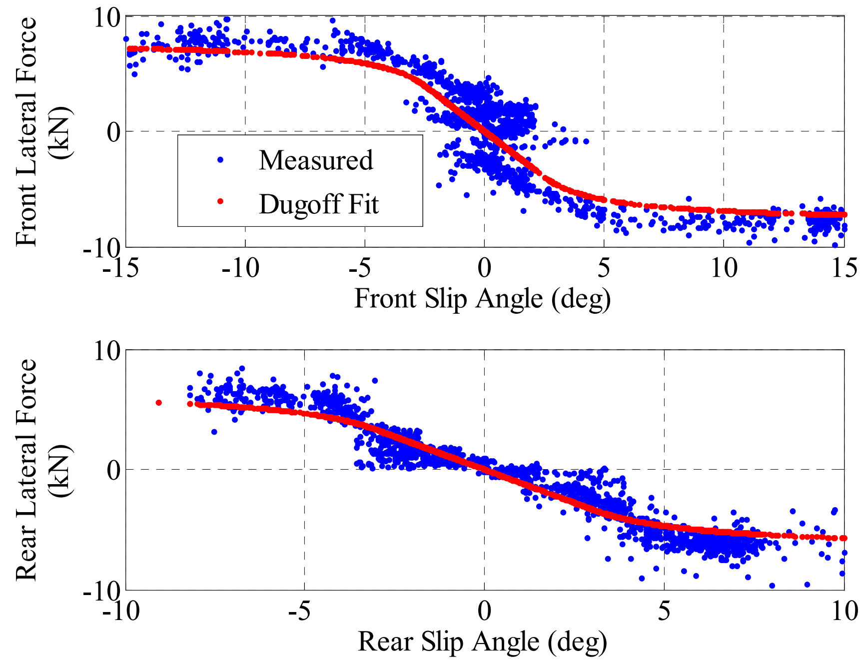


Tire Estimation

Simulated vs. Experimental Vehicle Data



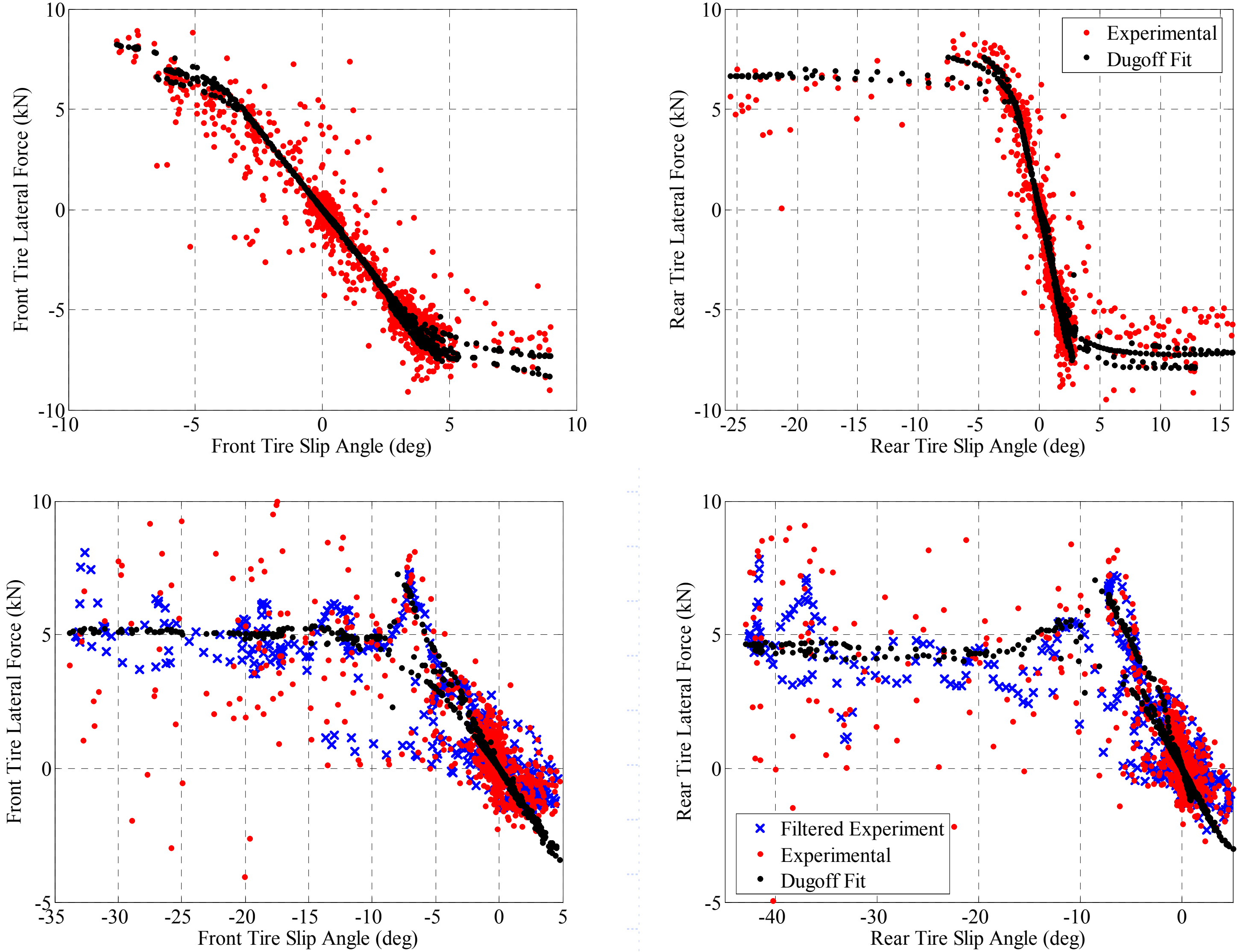
Experimental Data vs. Estimated Tire Model



On-line Tire Curve Estimation

Asphalt

Gravel



Our newest high-speed UGV (Trained K-9):

AUBURN UNIVERSITY

GPS AND VEHICLE DYNAMICS LAB

http://gavlab.auburn.edu

High-Speed Driving of Prescribed-Routes

Chris Urmson

TARTAN RACING

Chris Urmson
Carnegie Mellon University

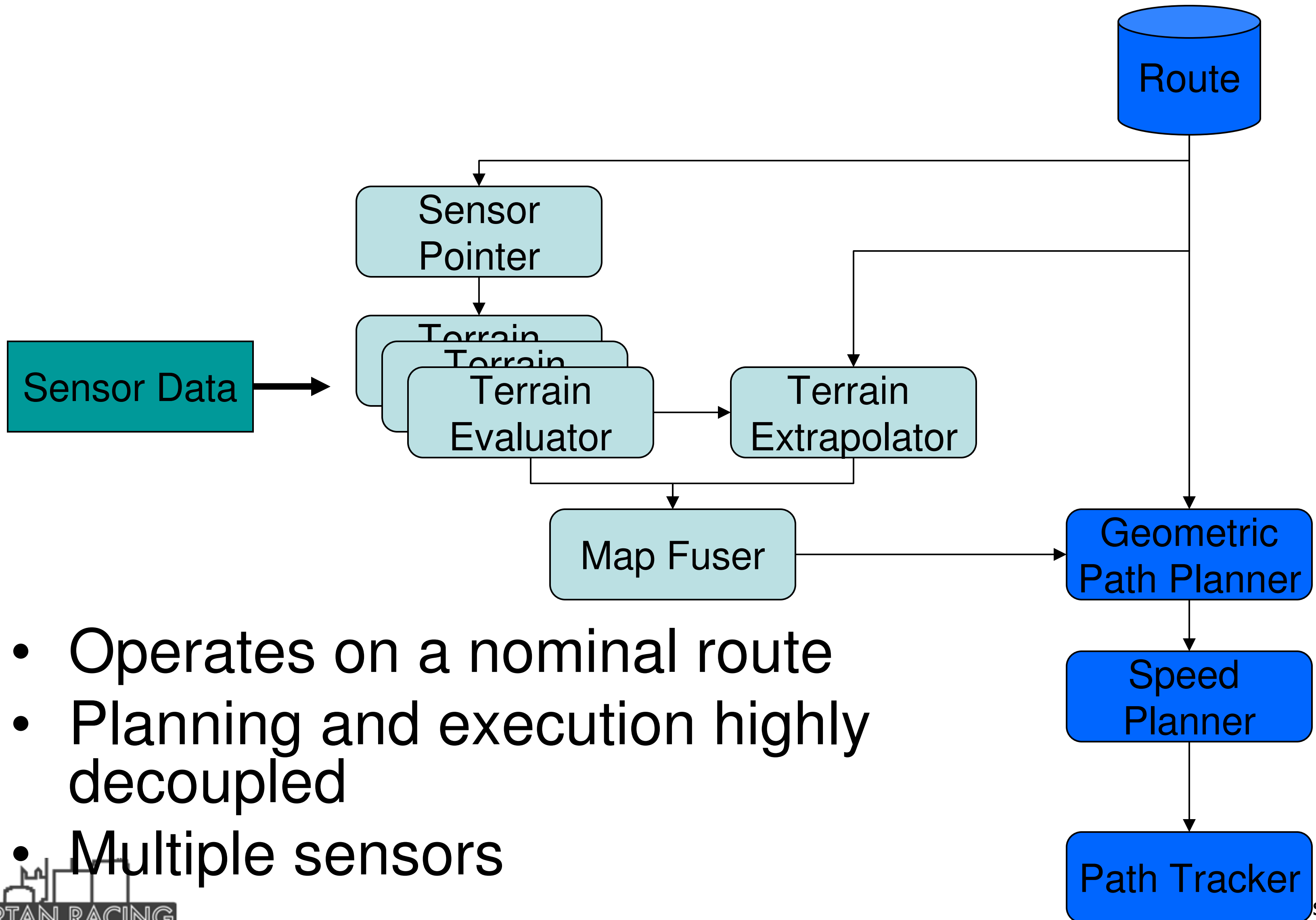
Motivation

Chris Urmson
Carnegie Mellon University

GC Testing & Performance

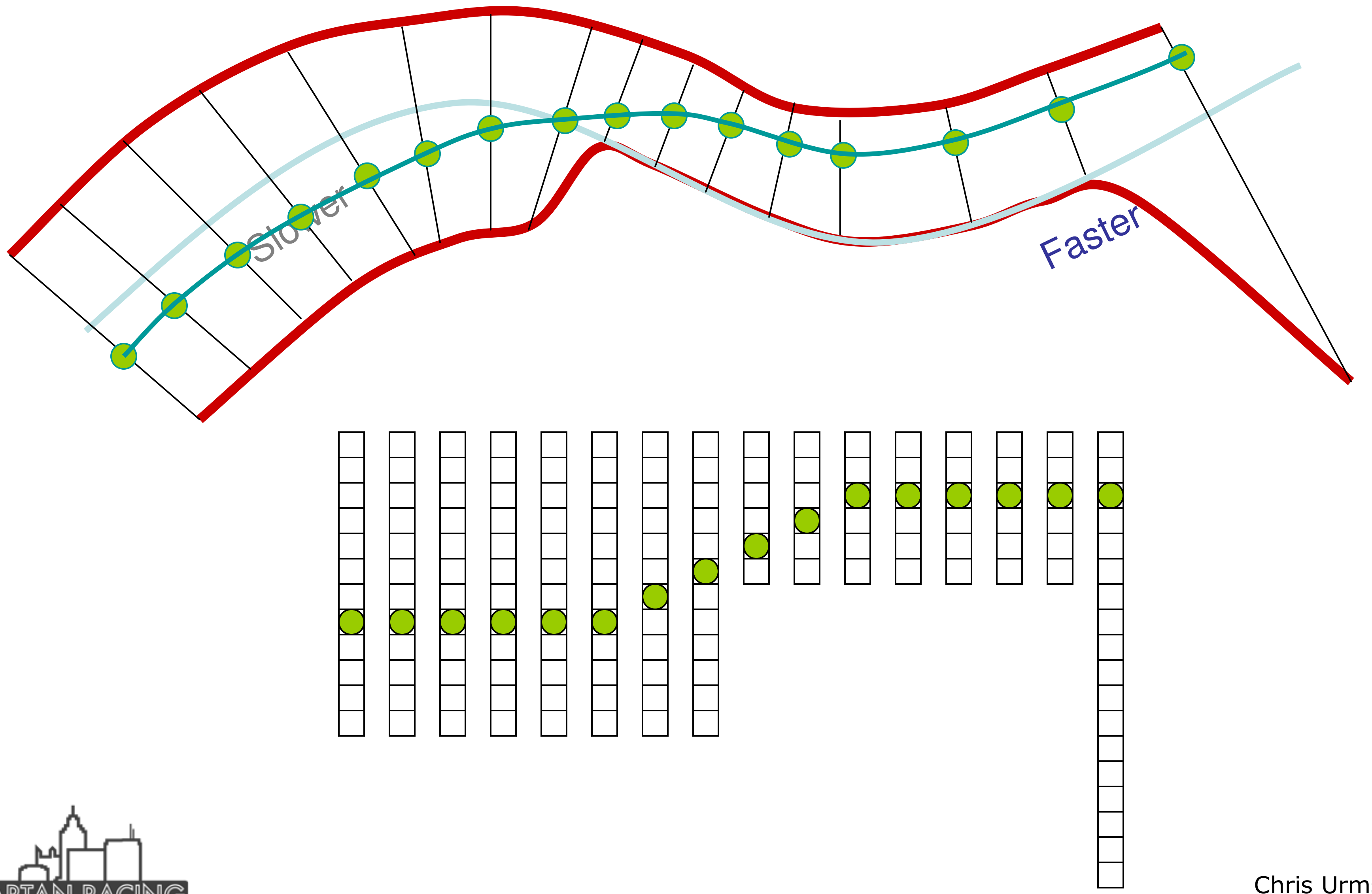
- About 6,000 miles total
  - 4500 for Sandstorm
  - 1500 for H1ghlander
- Greatest distance
  - 178 miles in desert
  - 200 miles on race track
- Sustained speed: 35mph (13.5mps)
- Peak speed: 50 mph
- Challenge:
  - 132miles/7 hours
  - ~19 mph

Driving Software



- Operates on a nominal route
- Planning and execution highly decoupled
- Multiple sensors

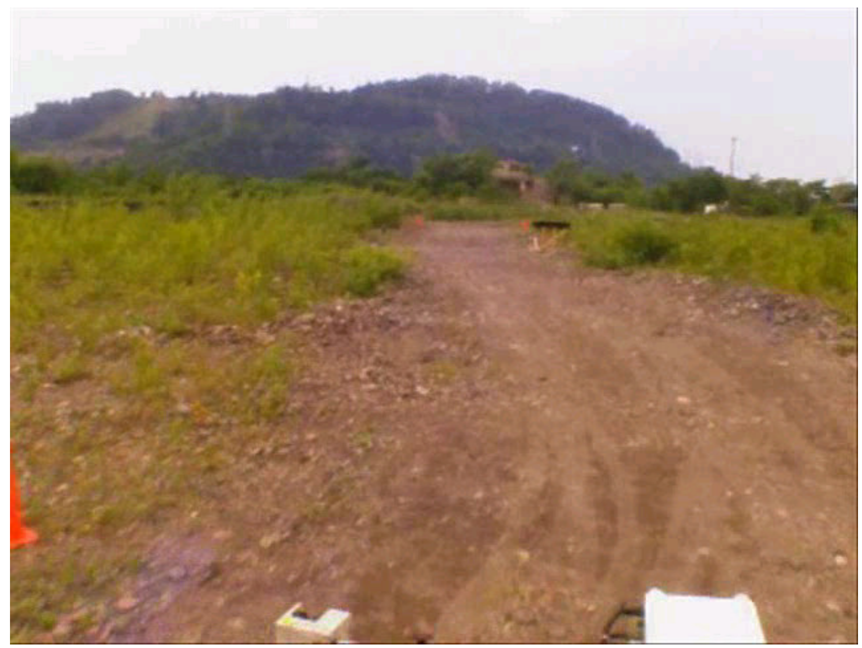
Conformal Path Planning



Chris Urmson
Carnegie Mellon University

Speed Planning & Tracking

- Speed Control
  - Limit execution speed based
    - flat earth slip and roll over bounds
    - deceleration limits to achieve speed limits
- Path Tracking
  - Pure pursuit with integral correction term



TARTAN RACING

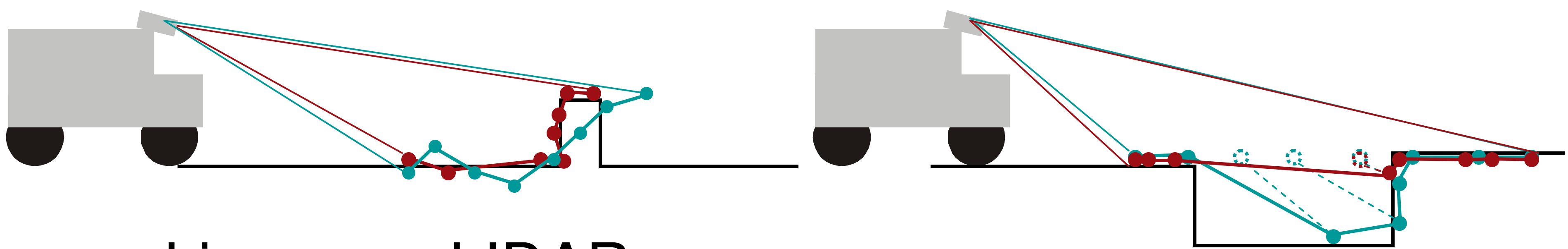
Beyond the Grand Challenge

- GC speeds approached limit of performance given sensing technology

TARTAN RACING

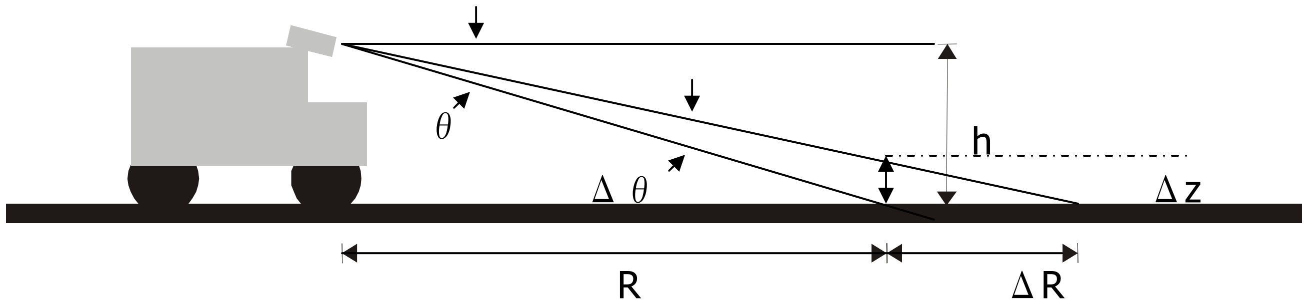
Chris Urmson
Carnegie Mellon University

The problem with Sensors

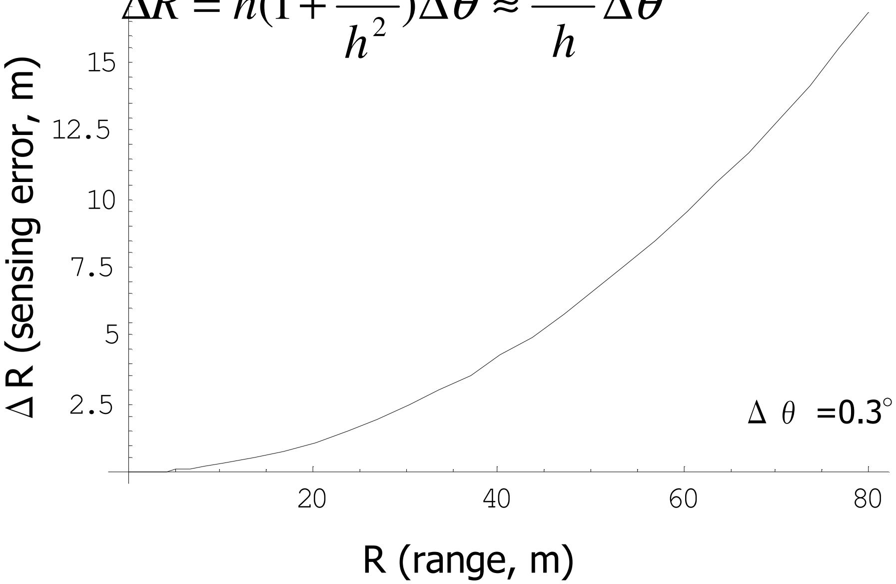


– Line-scan LIDAR
  - Good measurement accuracy
  - Irregular density of measurements
– Stereo-vision
  - Poor measurement accuracy
  - Good density of measurements

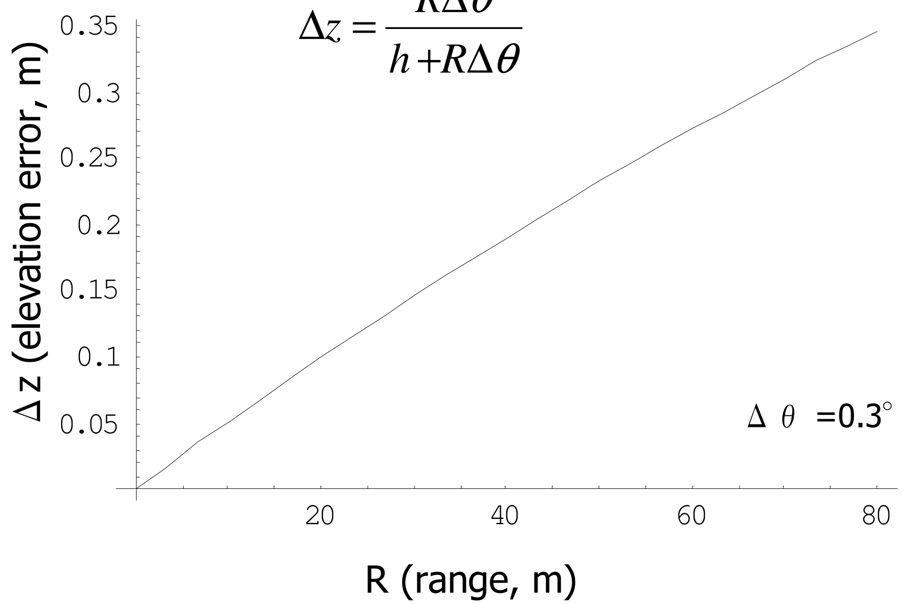
Point Density: LIDAR



$$\Delta R = h\left(1+\frac{R^2}{h^2}\right)\Delta\theta \approx \frac{R^2}{h}\Delta\theta$$



$$\Delta z = \frac{R\Delta\theta}{h+R\Delta\theta}$$



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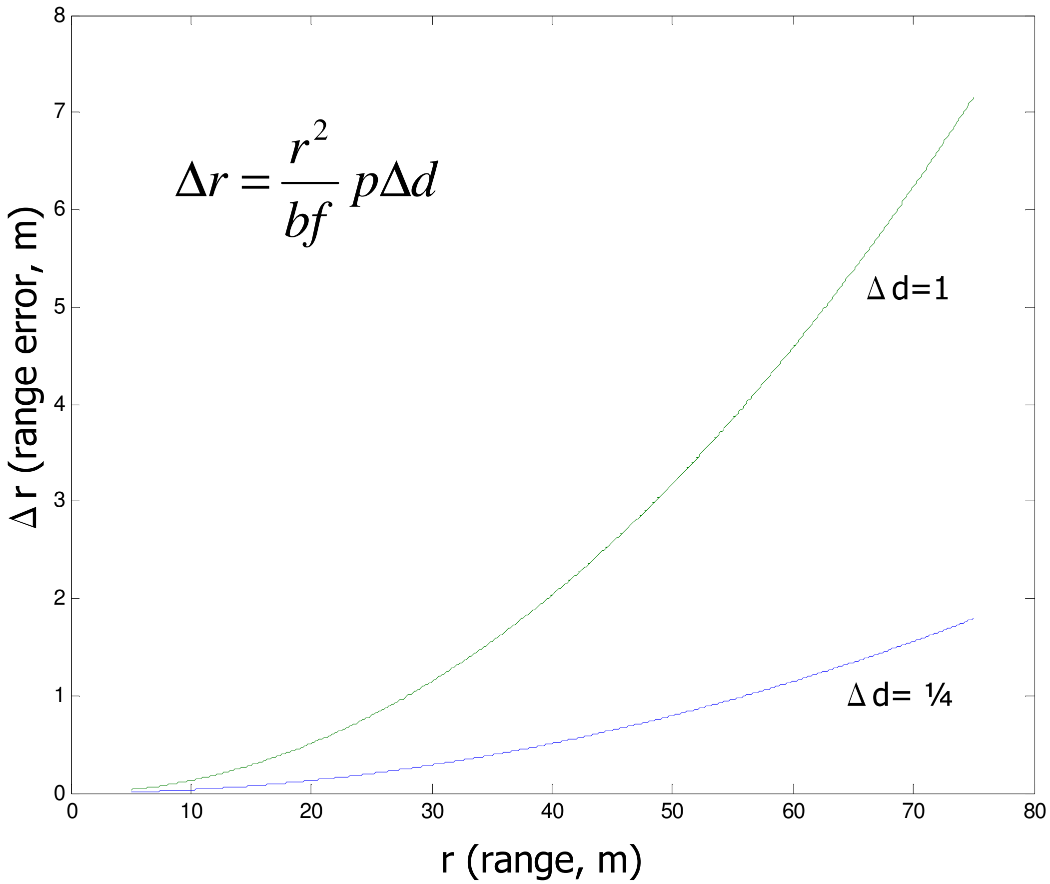
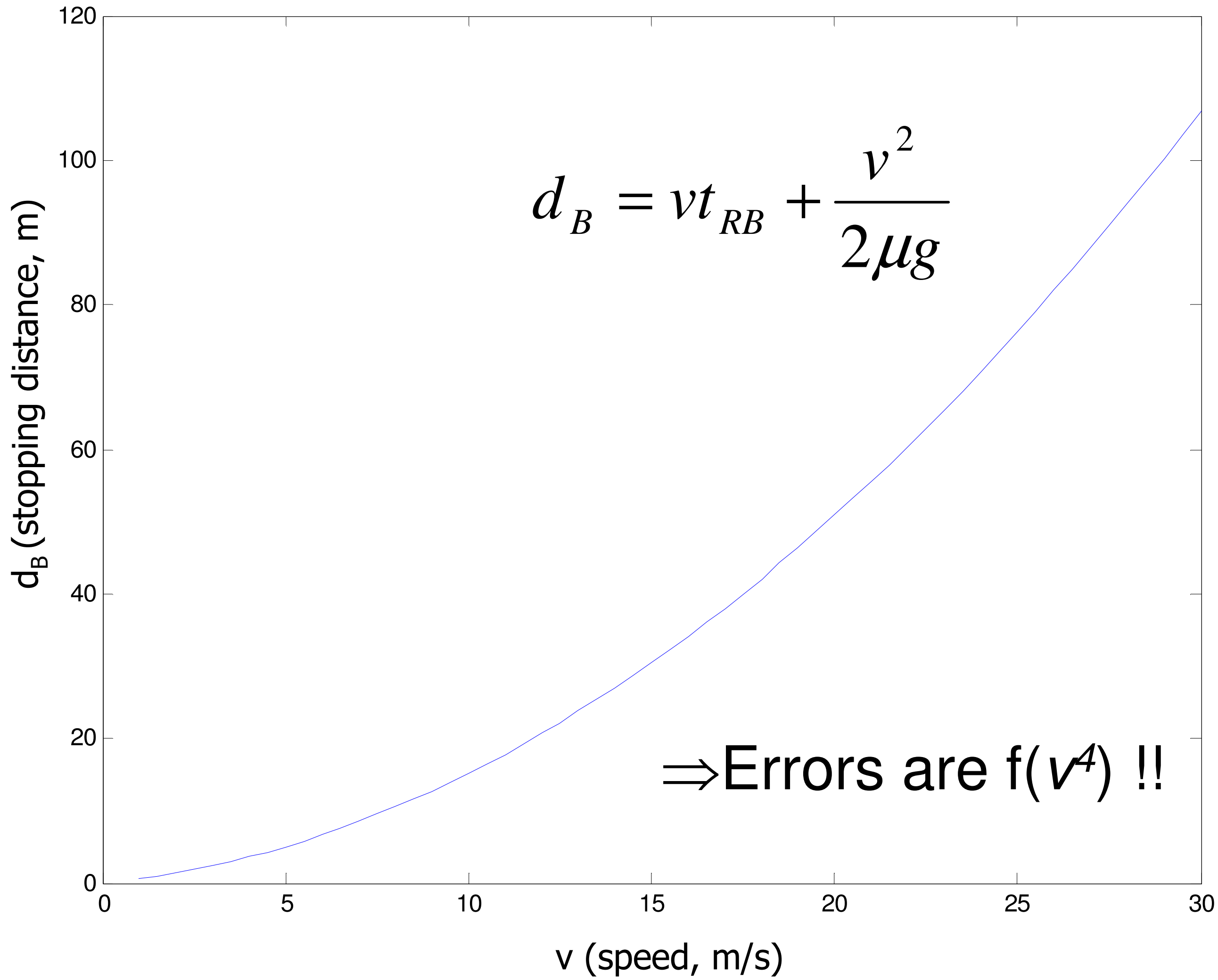
Range Error: Stereo Vision



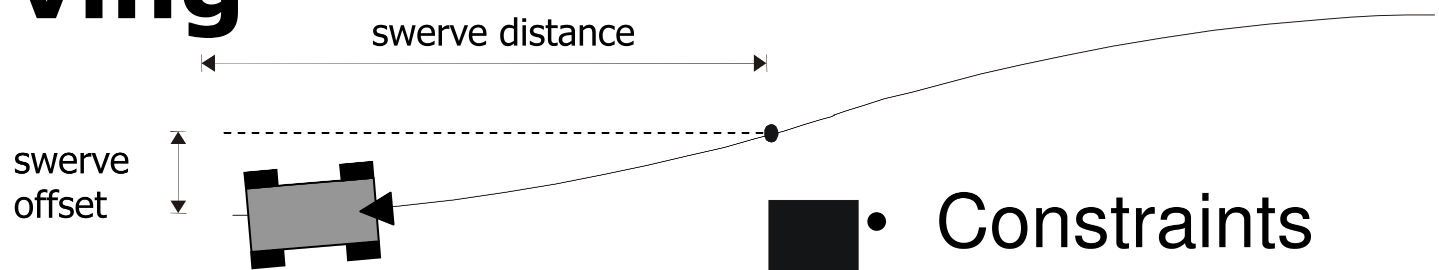
Parameter	Value
Baseline (b)	50cm
Focal length (f)	11mm
CCD pixel size (p)	7µm

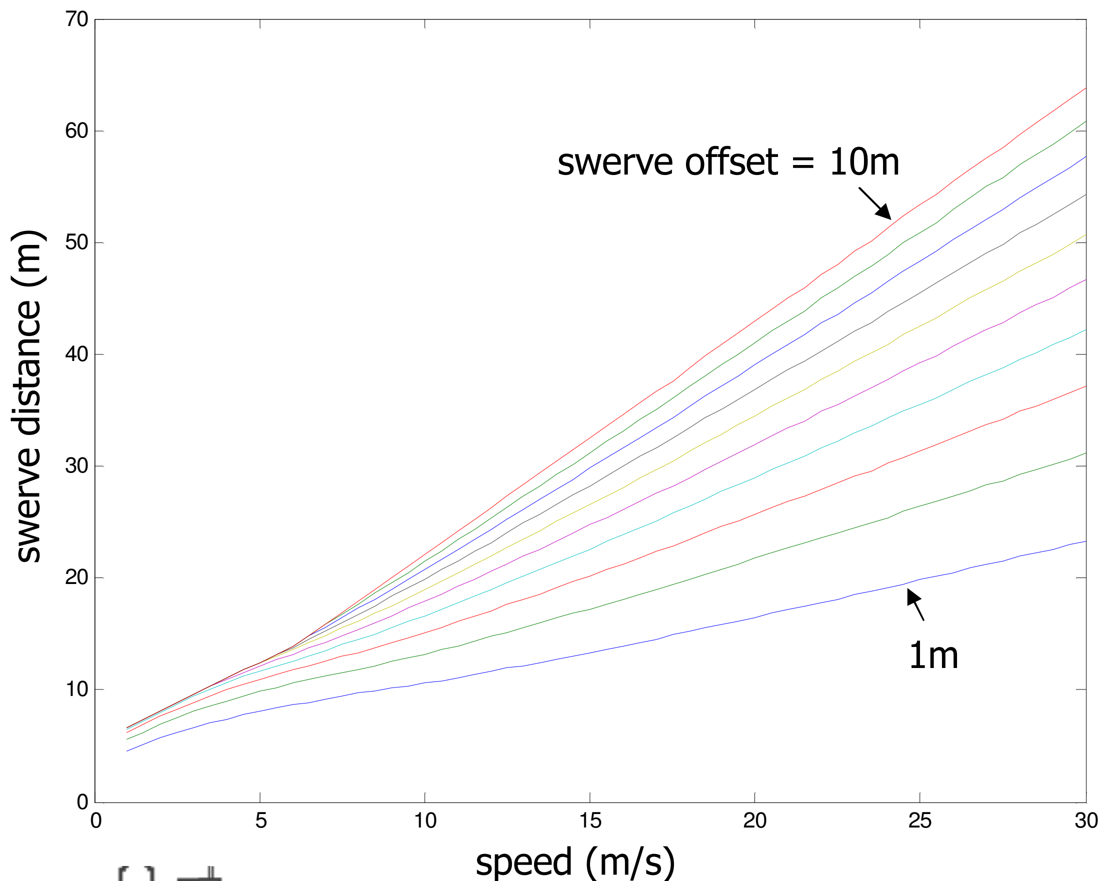
Stopping



Legend	
t_{RB}	Braking reaction time
μ	Coefficient of braking
g	Gravity

Swerving





- Constraints include:
  - kinematic curvature limits
  - tip-over and slip curvature limits
  - steering slew rate limits
  - reaction time

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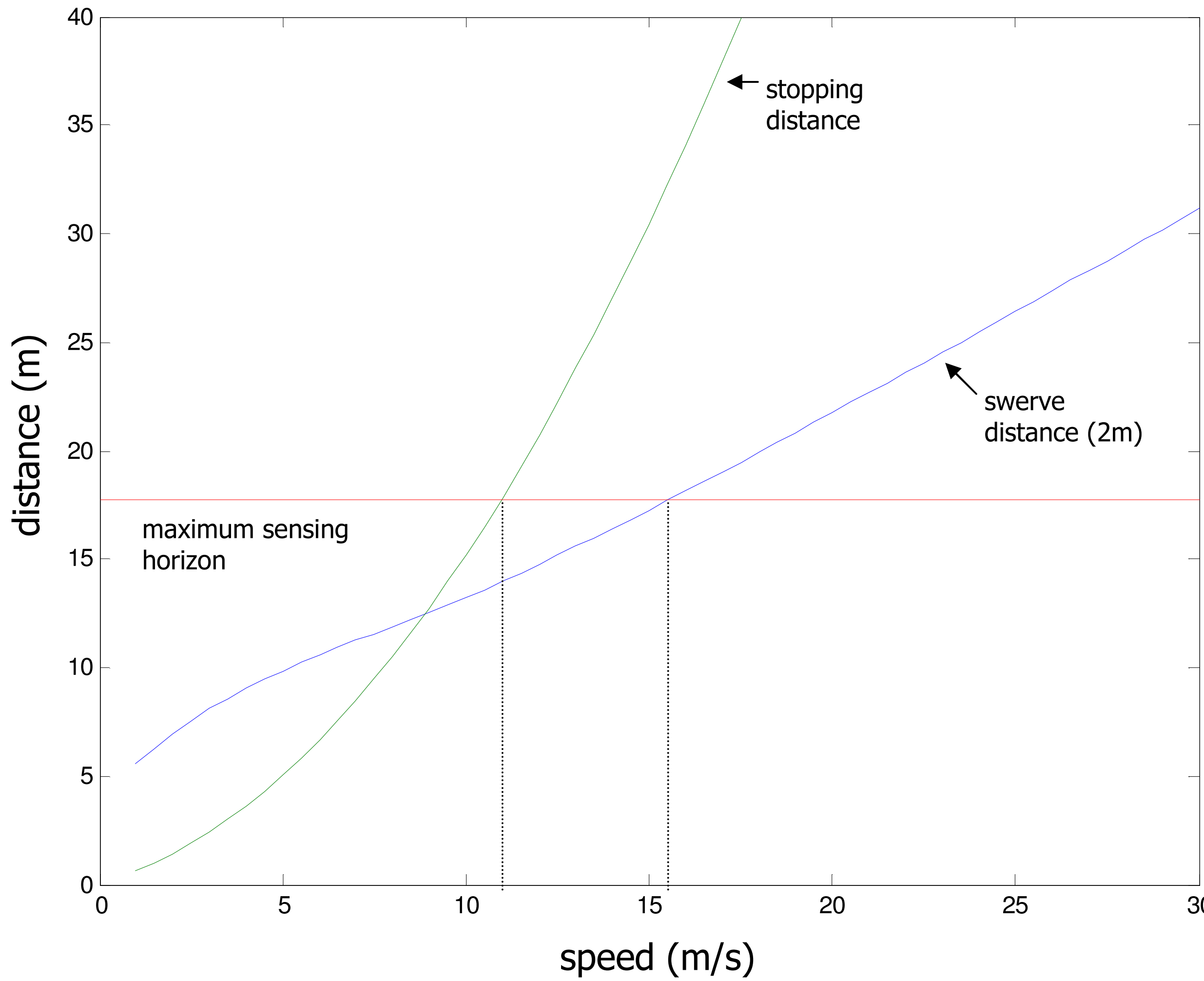
Carnegie Mellon University

Improving Performance

System Characteristic	Value
Swerving reaction time	0.1s
Kinematic curvature limit	0.2 m^{-1}
Maximum slew rate	0.067 $m^{-1}s^{-1}$
Coefficient of friction	0.5
Gravity	9.8 m/s^2

$$d_{max} \equiv vt + \frac{v^2}{2\mu g}$$



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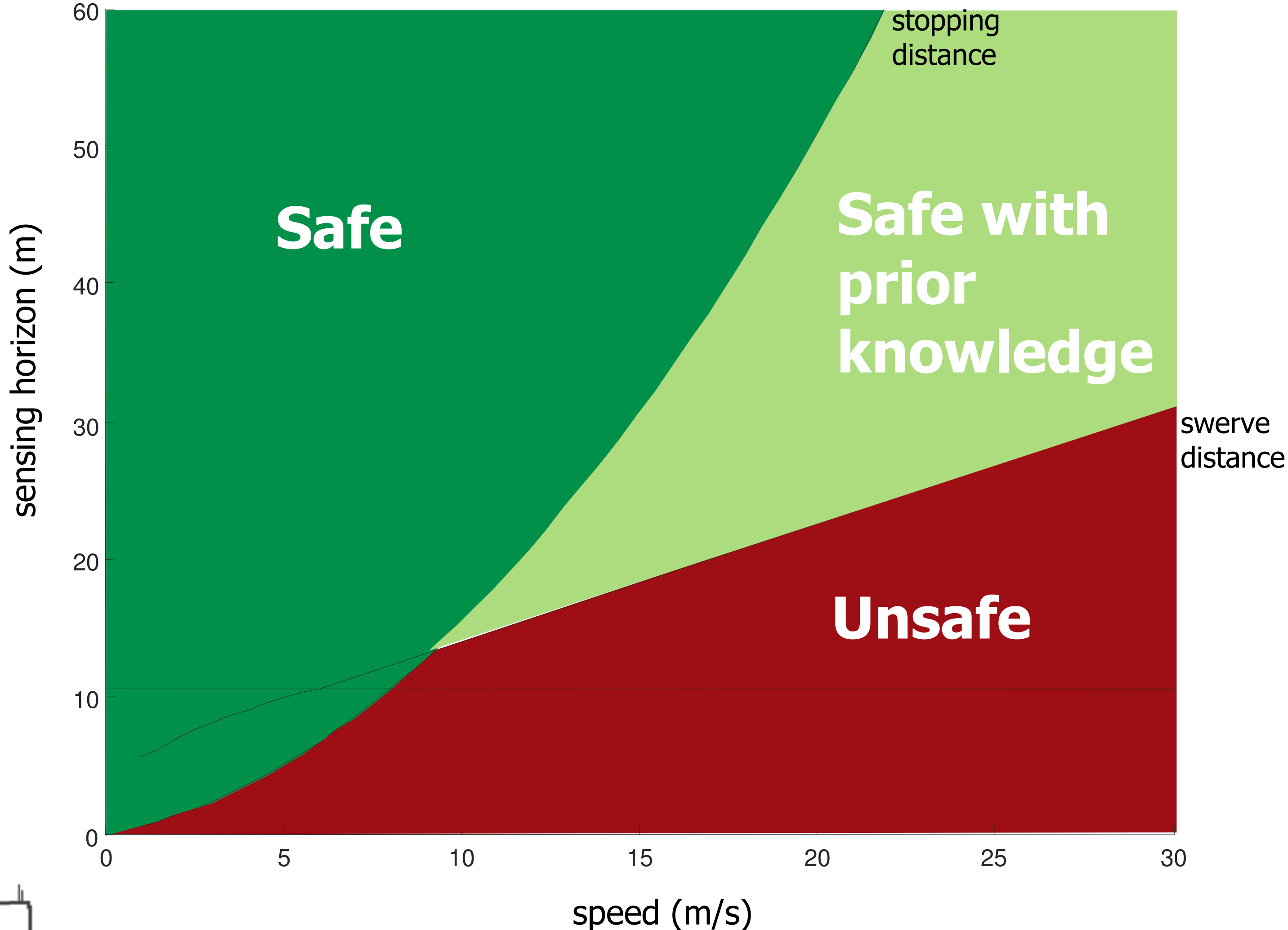
Space of Navigation



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Carnegie Mellon University

Control of Autonomous Mobile Robots in Unknown Terrain: Past Research, Future Challenges

Laura Ray

Workshop on Mobility and Control in Challenging Environments

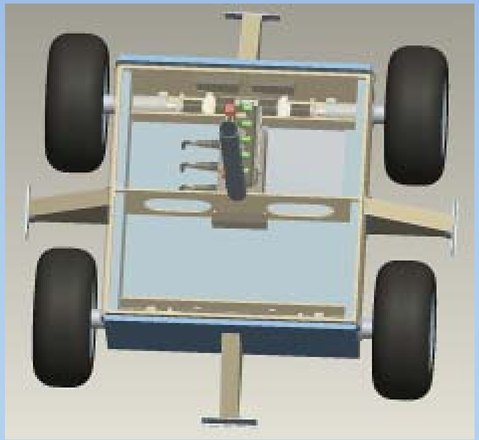
Olin College, Needham MA

October 5-6, 2006

THAYER SCHOOL OF ENGINEERING AT DARTMOUTH

Outline

- *Cool Robot* – lessons in design of a high longevity, low-cost robot
- Terrain diagnostics and mobility
- Terrain characteristics and high-speed cooperative control
- Work in progress

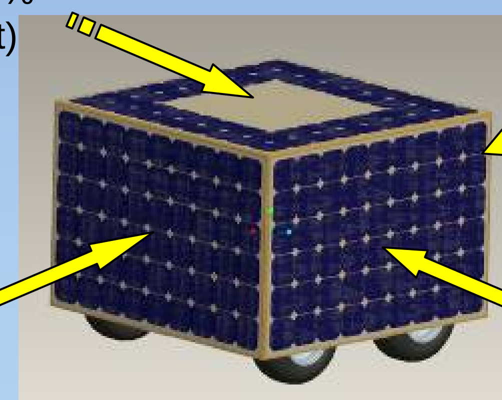


Cool Robot Design Overview

Summer Deployment of Instrument Networks

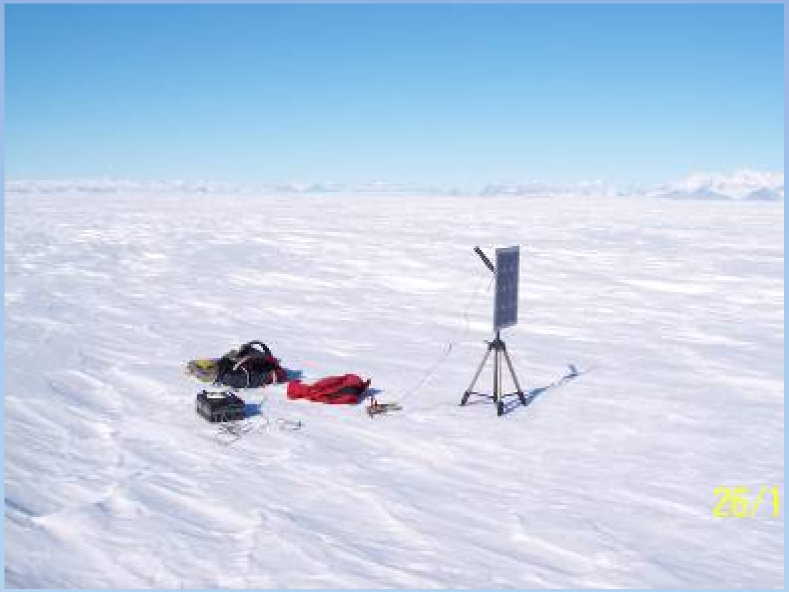
- 15 kg payload (or 40 kg towed), 75 kg vehicle
- 500 km in 2 weeks (0.4 m/s), max. 1 m/s
- Twin Otter transport
- Inexpensive (< $20k)
- Generates ~100 – 340 W
- GPS Navigation and Smart Mobility without vision

270 W electrical power @ 20° sun elev.
35% is reflected power



Terrain Characteristics

- Common *sastrugi* - 10 – 30 cm on 1 – 3 m scales
  - — do not present mobility issues (good traction & clearance)
  - — affect power consumption, control & navigation
  - — 100’s km without sastrugi
- Chart routes around large sastrugi



Mobility Design

- Four wheel, direct drive
  - — efficient, simple, good traction
  - — ATV tires run flat, < 20 kPa (3 psi)
- Lightweight construction (low resistance)
  - — target 75 kg, actual 60 kg
  - — target R/W = 0.24, actual R/W = 0.21 Summit, Greenland snow
- Sensors for “smart mobility”
  - — tilt, sinkage, gyrocube,
  - —motor current, panel power
  - — temperature, wind speed/direction

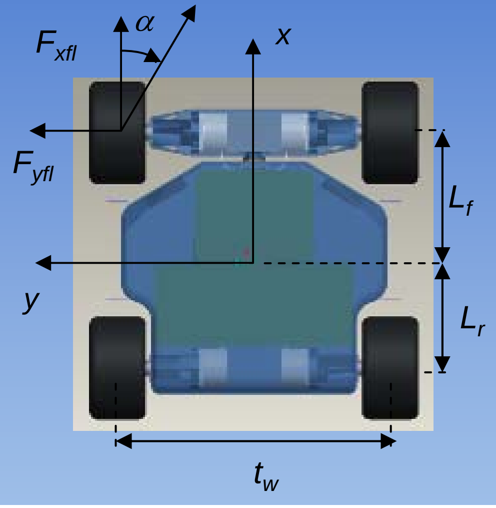

Smart Mobility

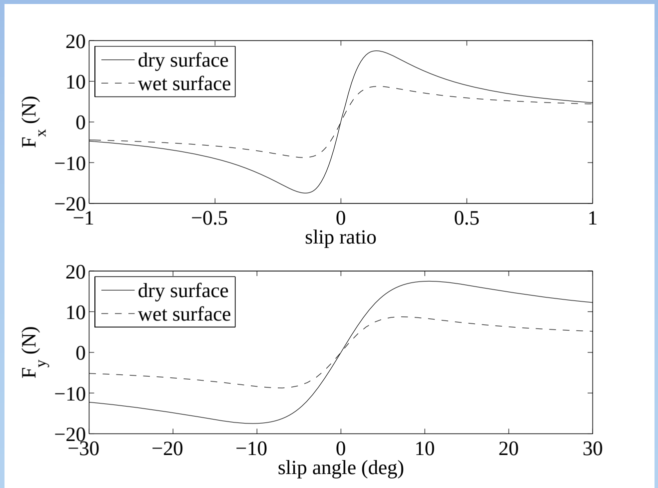
What can I measure *in-situ* to

- estimate maximum attainable speed
- estimate maneuverability
- avoid immobilization
- retain/augment stability
- maintain stability/performance of group dynamics (cooperative control) at high speed

Tire-Terrain Characterization from Vehicle Performance

- Rigid-body dynamics are well-known
- Tire/track forces are influenced by terrain





Rigid Terrain Model:

$$\dot{v}_x = v_y r + \frac{1}{m}\left(F_{xfl} + F_{xfr} + F_{xrl} + F_{xrr}\right)$$

$$\dot{v}_y = -v_x r + \frac{1}{m}\left(F_{yfl} + F_{yfr} + F_{yrl} + F_{yrr}\right)$$

$$\dot{r} = \frac{1}{I_{zz}}\left[\left(F_{xfr} + F_{xrr} - F_{xfl} - F_{xrl}\right)\frac{t_w}{2} + \left(F_{yfr} + F_{yfl}\right)L_f - \left(F_{yrl} + F_{yrr}\right)L_r + M_z - M_{res} r\right]$$

$$\dot{\omega}_{fl} = \left(T_{fl} - RF_{xfl} - b\omega_{fl}\right)\frac{1}{I_w}$$

→ With appropriate sensor suite, tire forces are observable.

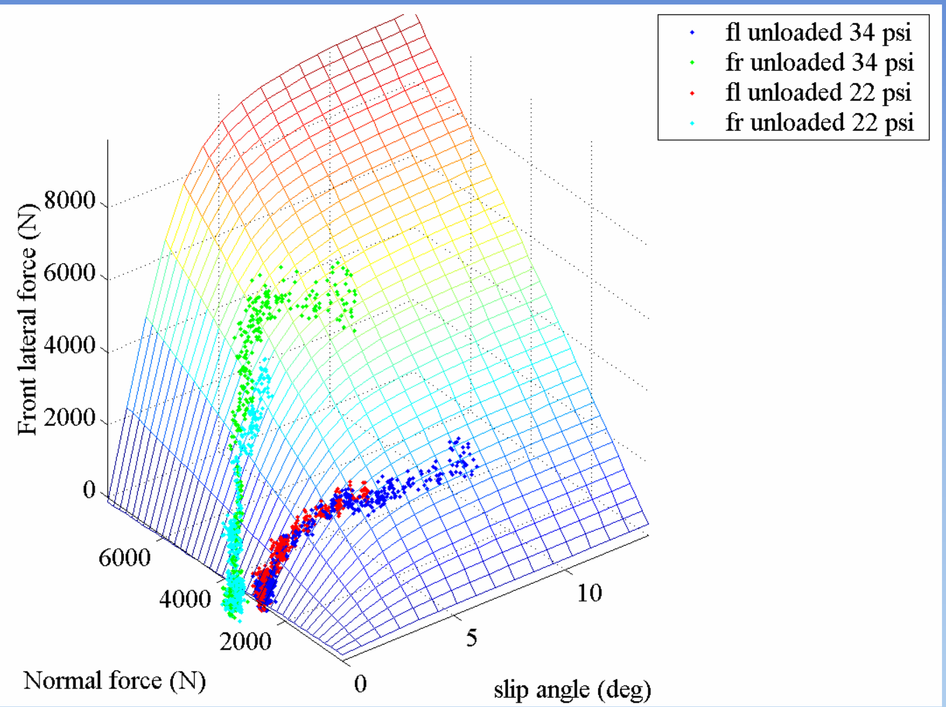
Extended Kalman-Bucy Filtering for Tire Force Estimation

- **Sensors – *x* and *y* accelerations, yaw rate, wheel speeds, vehicle speed, inputs**
- **Augment rigid-body dynamics with tire forces as random walk model**
- **Implement five-step filter**
  - Propagate dynamics → state estimate
  - Propagate covariance → covariance estimate
  - Compute filter gain
  - Update state estimate
  - Update covariance
- **Compute wheel slip/slip angle from state estimate**

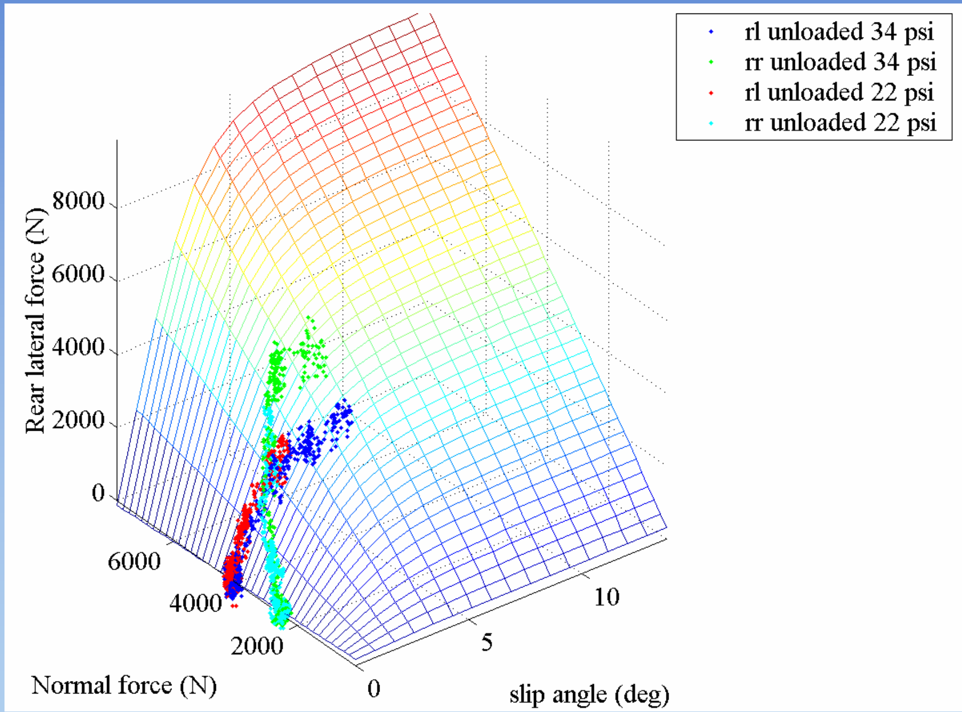
Originally developed and tested for off-line estimation

Estimated Lateral Force vs. Slip Angle and Normal Load for Two Tire Pressures

Front



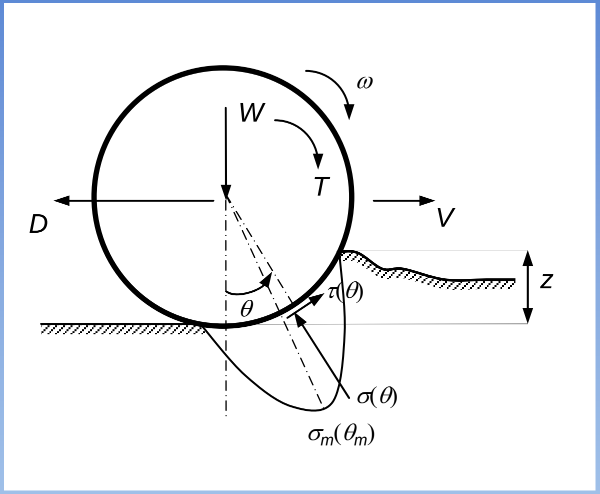
Rear



Terrain Diagnostics

- **Semi-empirical theory (Bekker, Wong) models motion in deformable terrain (1950's, 60's)**

- **Shear stress and normal stress are functions of terrain parameters**
  - Cohesion
  - Friction angle
  - Shear deformation modulus
  - Sinkage parameter(s)
  - Stress distribution parameters



- **Traction and resistance depend on stress distributions**

- **Dynamic/transient effects not modeled**

Estimation before Modeling

- **Decouples force-slip estimation from semi-empirical model**
  - Tests validity of model with a range of data/terrain characteristics

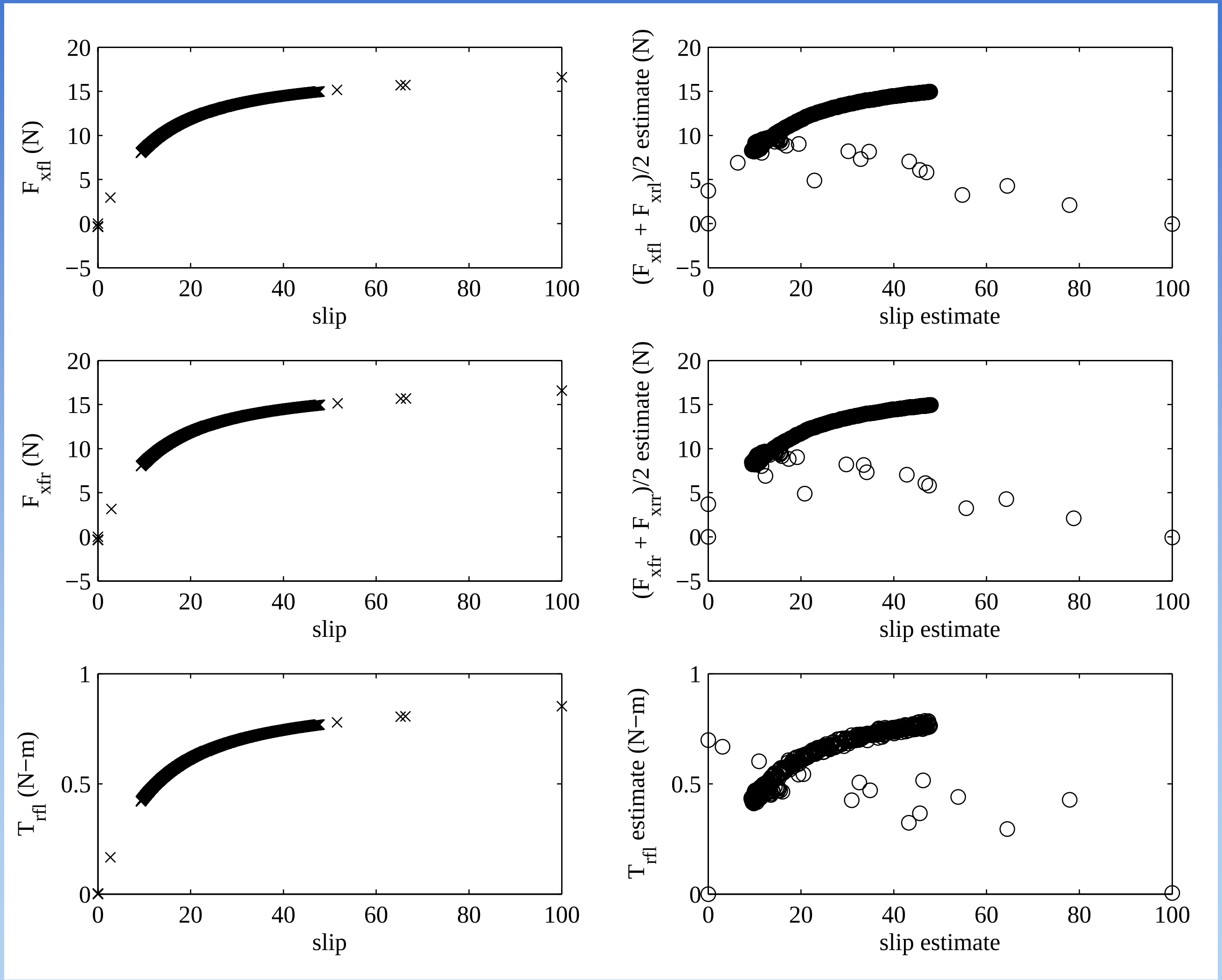
- **Real-time implementation provides force-slip characteristics independent of terrain**
  - Gets to heart of stability augmentation and “peak seeking” control
  - …but still allows for identification of terrain via existing terrain parameters
  - May be possible to identify terrain based on “normal” maneuvering that is sufficiently rich

Example Estimation Results –

Net Long. Force and Torque vs. Slip for longitudinal motion on "lean clay"

Actual

Estimated



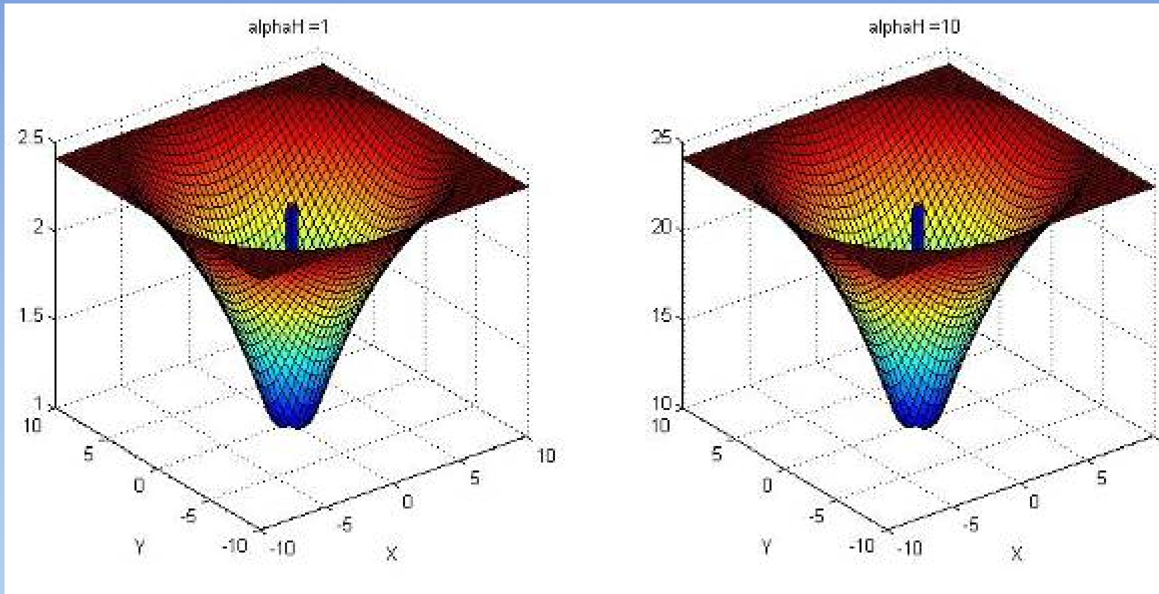
Terrain Diagnostics and High-Speed Cooperative Control

- Potential Function Approach – scalar gains control applied force magnitude

$$T(r,\dot{r}) = -\nabla V(r) + d(r,\dot{r})$$

$$V_d = \begin{cases} \alpha_d \left(\ln(r_{ij}) + \dfrac{d_o}{r_{ij}} \right) & 0 < r_{ij} < d_1 \\ \alpha_d \left(\ln(d_1) + \dfrac{d_o}{d_1} \right) & r_{ij} \geq d_1 \end{cases}$$

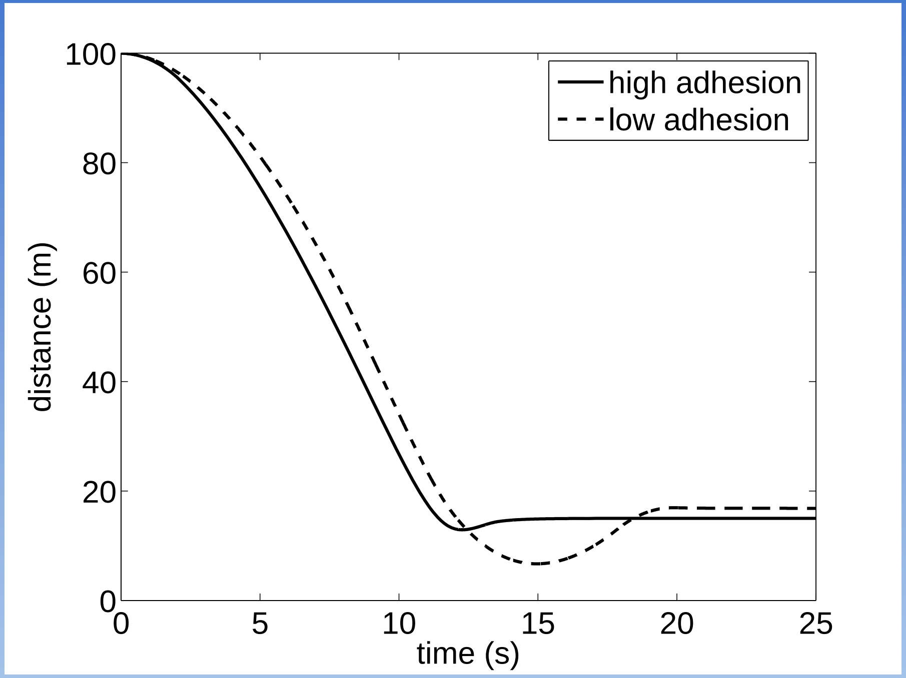
$$V_h = \begin{cases} \alpha_h \left(\ln(h_{ik}) + \dfrac{h_o}{h_{ik}} \right) & 0 < h_{ik} < h_1 \\ \alpha_h \left(\ln(h_1) + \dfrac{h_o}{h_1} \right) & h_{ik} \geq h_1 \end{cases}$$

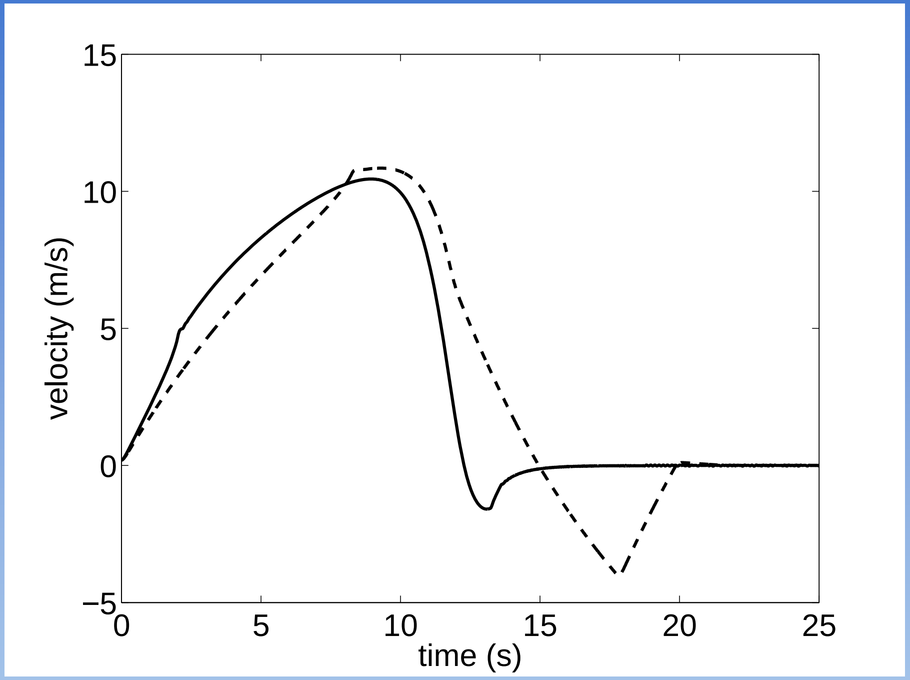


Testbed for Dynamic Cooperative Control and Terrain Diagnostics

- 4WD, passive joint
- Comparable performance to "Dragon Runner"
  - speed ~10 m/s
  - yaw rate ~1 rev/sec
  - acc ~ 7 m/s^2 (hard surface)
  - Parts cost ~ $5k per robot
- Plastic-molded chassis w/ "drop-in" components
- M = 12.4 kg
- Sensors: GPS, angular rates, linear accelerations, magnetic compass, motor currents, wheel speed
- 7 robots, wireless inter-robot communication

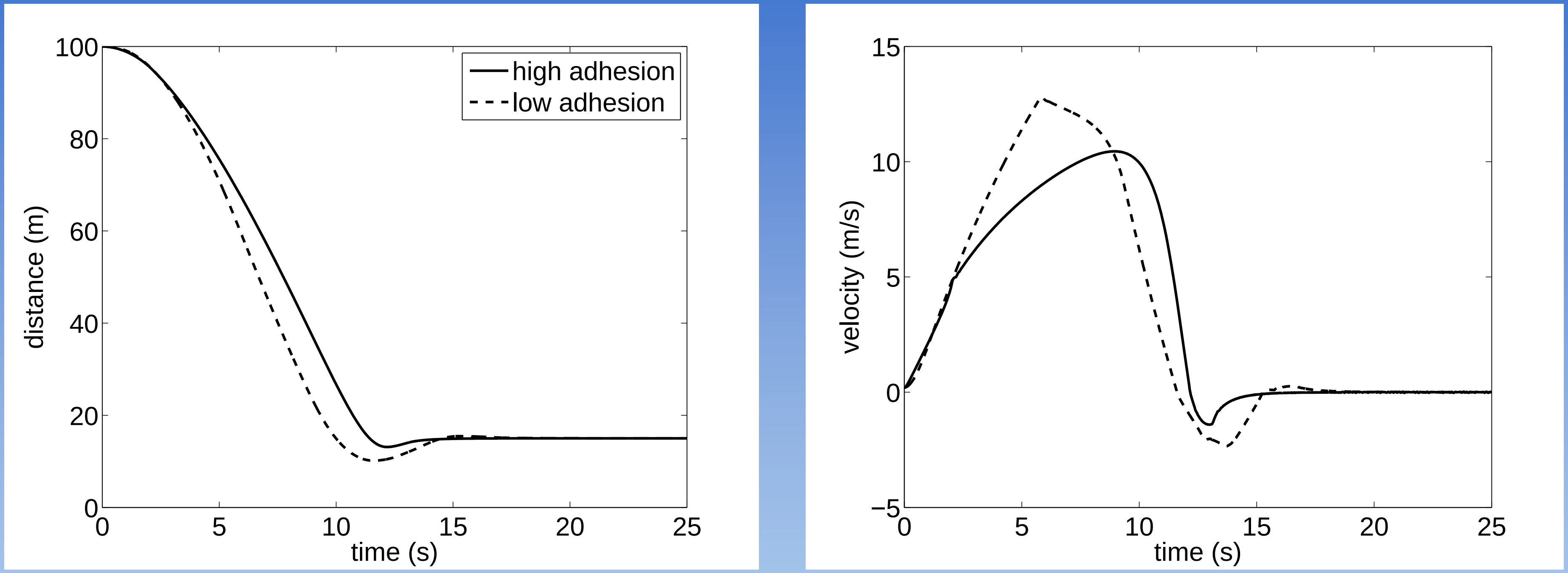
Example Trajectory - One Robot





Fixed potential function scalar gains

Example Trajectories for High and Low Adhesion Surfaces

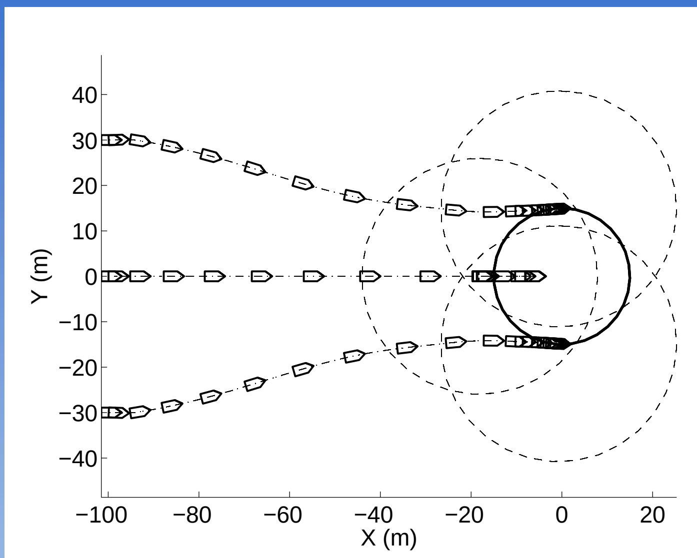


Fixed potential function scalar gains

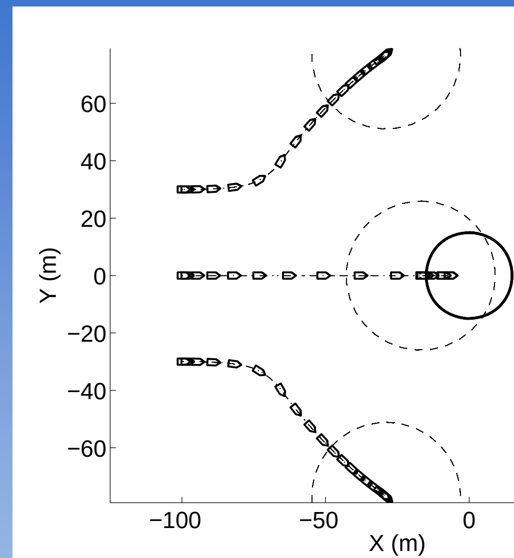
w/ local slip setpoint control

Group Dynamics

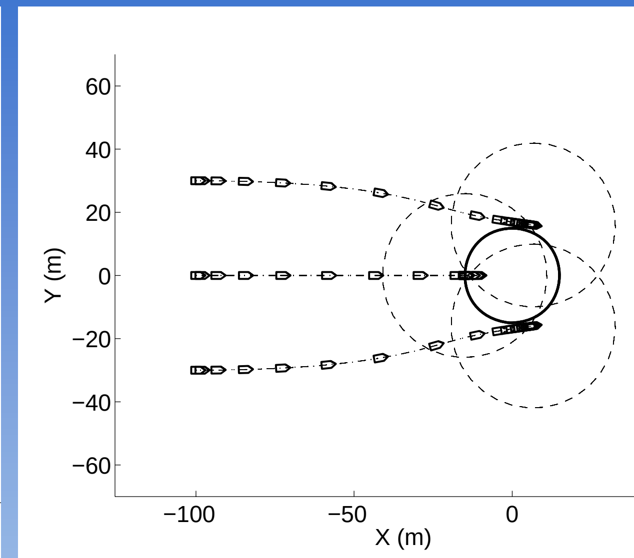
High adhesion



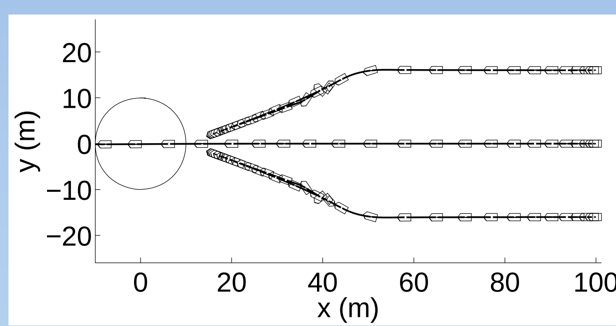
lower adhesion no slip control



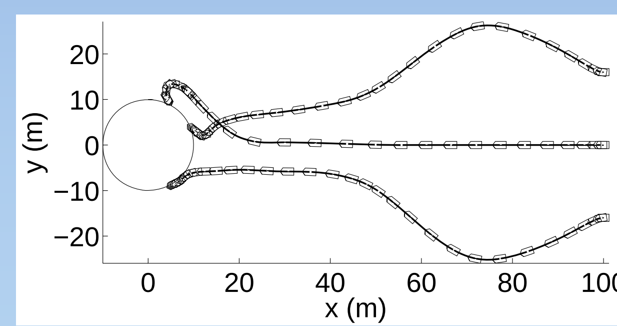
lower adhesion, slip control



Very low adhesion no slip control



Very low adhesion, slip control



Present and Future Research

- **Evaluation of terrain diagnostics**
- **Estimation/inference of terrain parameters from tire force estimates**
- **Scouting?**
  - Design light-weight inexpensive “scout” vehicle for terrain estimation, extrapolate to heavy vehicle
- **High-speed cooperative control**
  - Distributed estimation/sharing terrain information
  - Interplay between communication, latencies, terrain variation, and control performance

Acknowledgements

Dr. Jim Lever, CRREL

John Murphy, Ph.D. candidate

Devin Brande, M.S. candidate

James Joslin, M.S. candidate

Active Sensing of Terrain by a Crawling Robot: Optimizing Gait for Terrain Selectivity

Richard Voyles

University of Denver

Amy Larson

University of Minnesota

Motivation: Small Resource-Constrained Robots

SSR-RC
SAFETY*SECURITY*RESCUE
RESEARCH CENTER

- NSF SSR-RC
  - USF
  - UMN
- Medium-term Research
- Near-term Fieldability

Lebanon, IN
IN-TF1
Aug. 2003
NSF R4

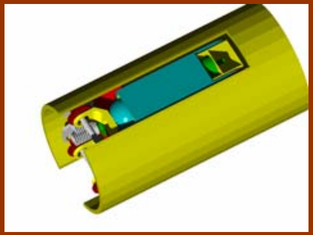
Lakehurst, NJ
NJ-TF1
Feb. 2005
NSF R4/SSR-RC

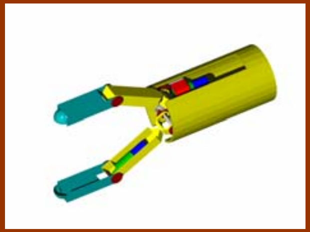
Example: CRAWLER to Augment Core-Bored Search

1. Bore Hole

2. Search Void with Camera

3. Search Occluded Spaces with Tethered Robot Dropped Through Bore Hole





CRAWLER crawling

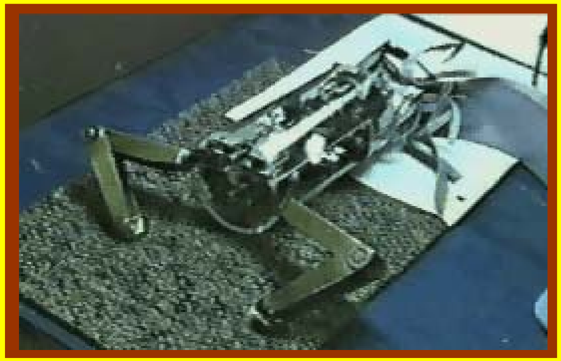
shown faster than real time

Objectives

- Small size needed for access tends to limit capability
  - Power, sensors, actuation, computation
- Adapt resources to compensate
  - Physical adaptation
  - Control adaptation

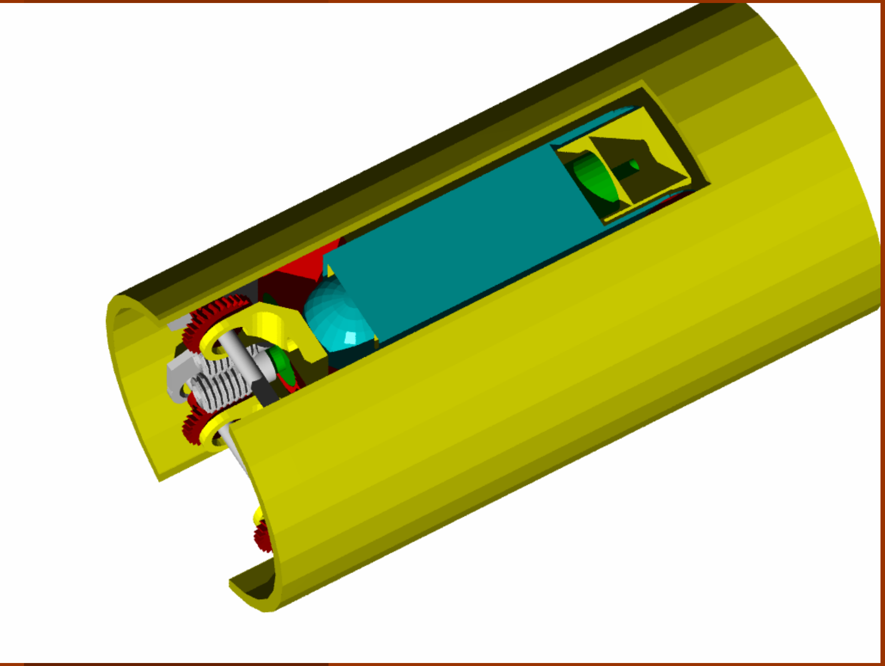
CRAWLER
a.k.a. TerminatorBot

- **Two 3-DoF Arms that Stow Inside Body**
- **Dual-Use Arms for both Locomotion and Manipulation**
- **Four Locomotion Gait Classes:**
  - **"Swimming" Gaits (dry land)**
  - **Narrow Passage Gait (no wider than body)**
  - **"Bumpy Wheel" Rolling Gait**
  - **"Body-Roll" Dynamic Gait**

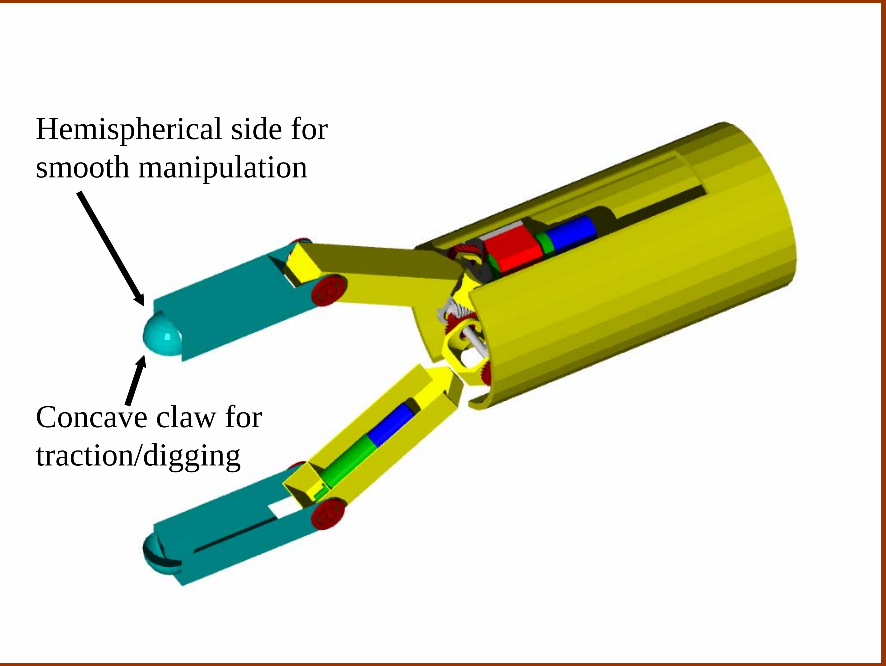


ThrowBot – Gross/Fine Locomotion

Stowed Configuration



Deployed Configuration

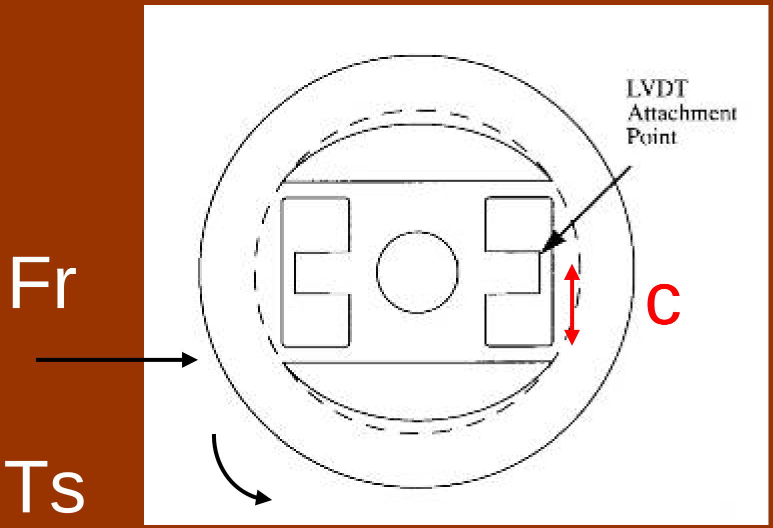


Barrel launching originated from DARPA Distributed Robotics Program.
Not actually hardened for throwing.

Novel Multi-Axis Force Sensors for Soil Probing

- $Ks = \dfrac{4Ea^3b(R^2+Rr+r^2)}{3(R-r)^3}$
- $\varepsilon = \dfrac{3(R-r)(5R+r)Ts}{16Ea^2b(R^2+Rr+r^2)}$
- $\dfrac{\varepsilon_s}{\varepsilon_n} = \gamma \dfrac{Ts}{Fr}$
- $\gamma = \dfrac{3(5R+r)((R-r)^2+a^2)}{8a(R-r)\,(R^2+Rr+r^2)}$

based on Vischer & Khatib, 1990



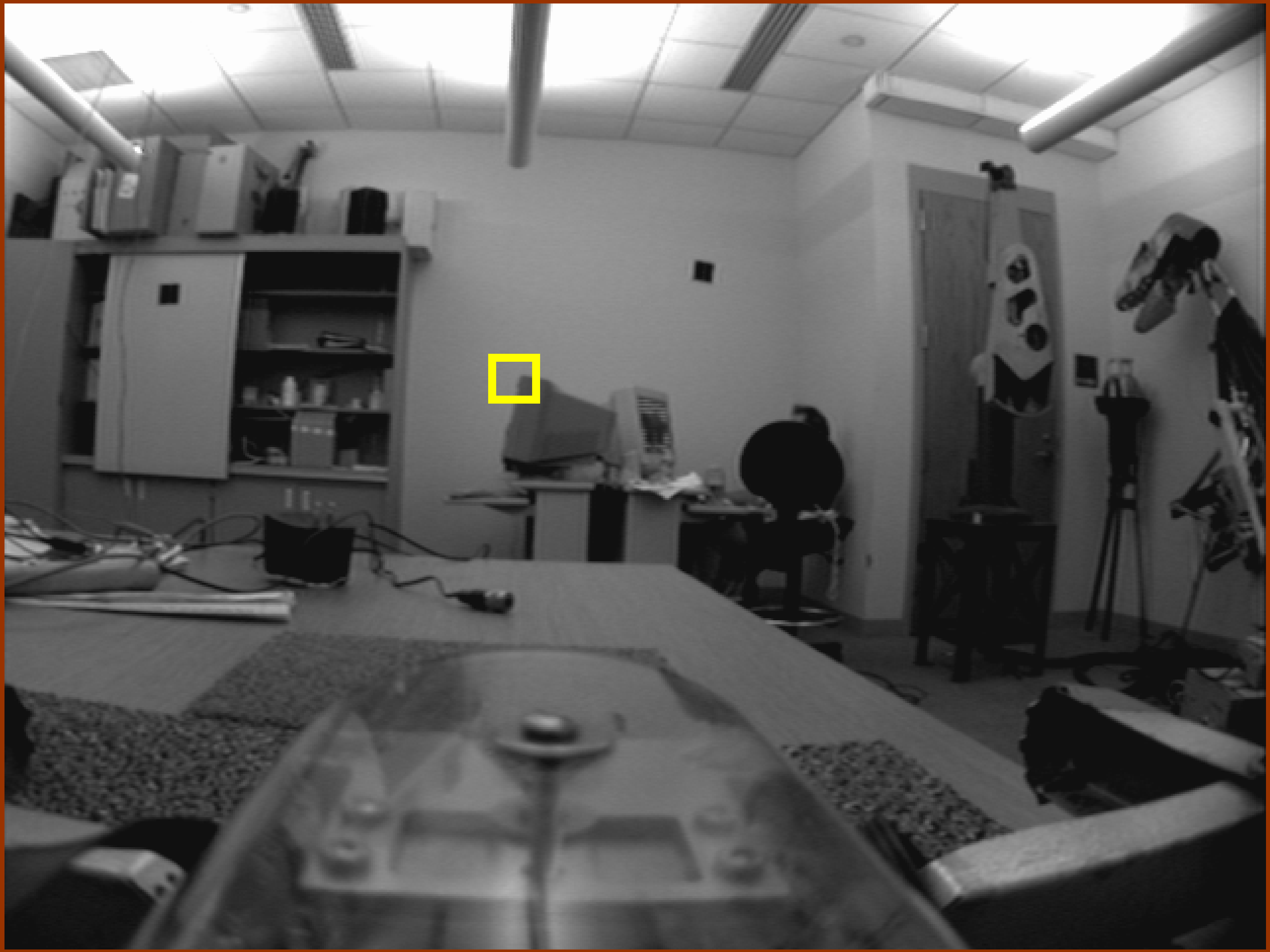
The *Gait Bounce* Terrain Metric

- **Measure?:**
  - **Tilt/Accel**
  - **Vision**

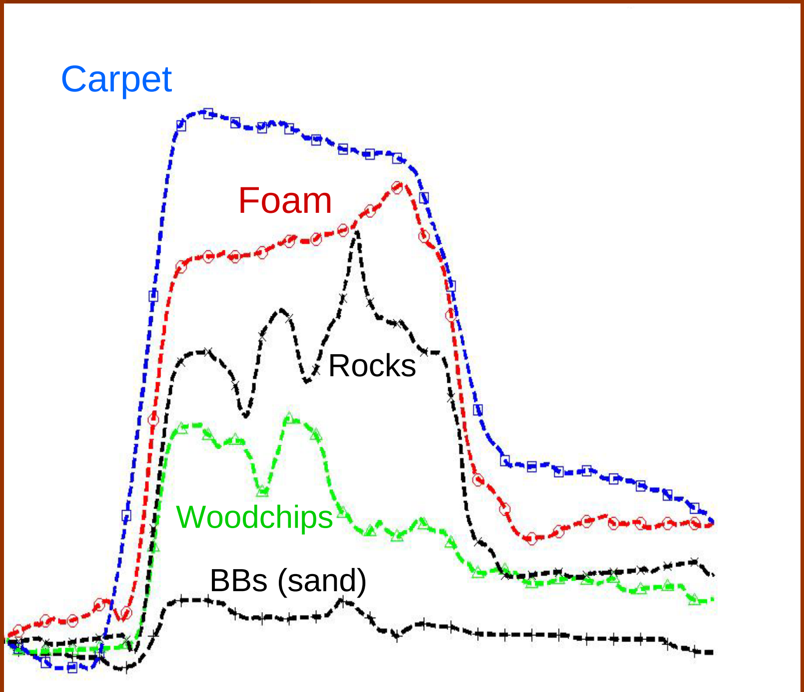
Robot's Eye View

Homing by Visual Servoing

- **Visual Servoing**
  - **2-D Sensor**
  - **1-D Problem**
- **Can we make use of the extra info??**



Gait Bounce Signatures and Alternatives



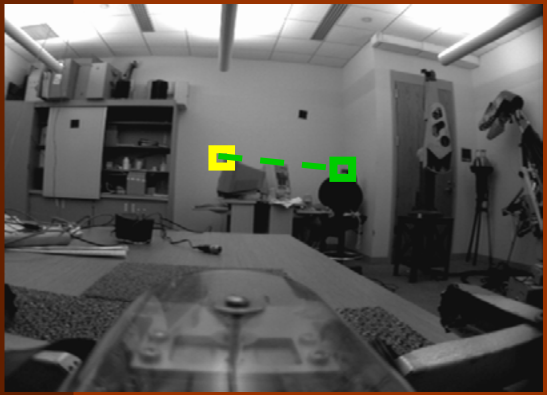
Gait bounce signature from various terrains.

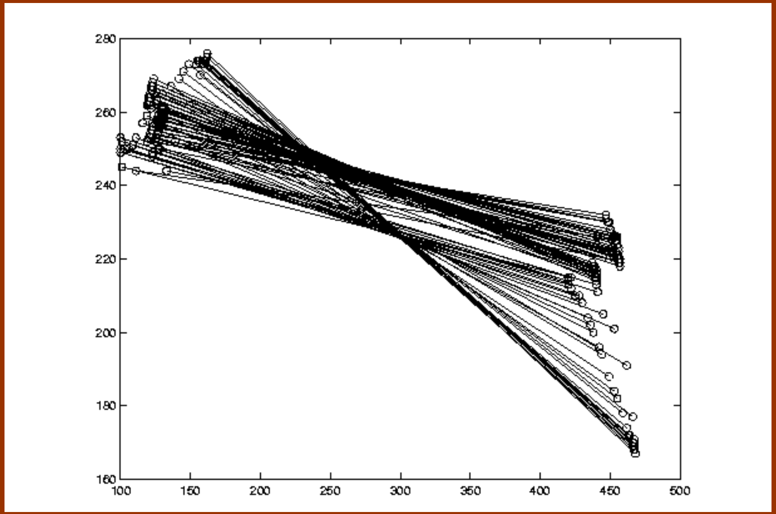
Other Work

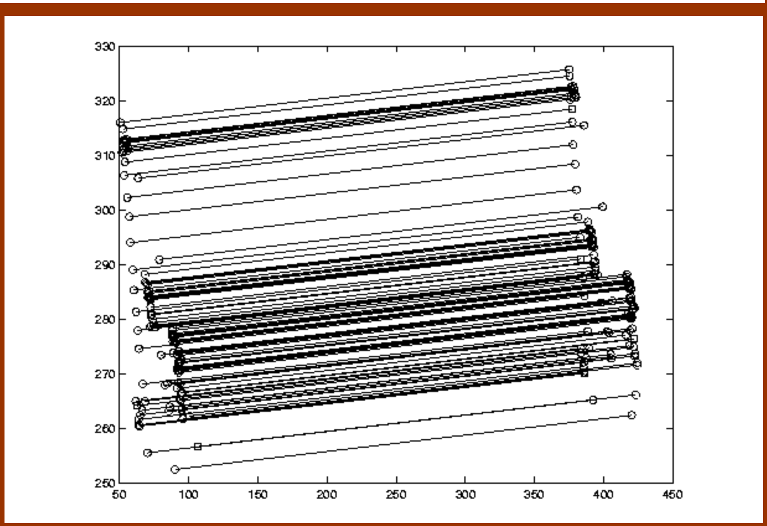
- **Looking Ahead (Vision)**
  - **Aerial and Elevation Maps (correspondence problem) – Gennery (1989), Kweon & Kanade (1992), Huber & Hebert (1999), …**
  - **Elevation Maps – Langer et al. (1994), Simmons et al. (1995), Gennery (1999), …**
  - **Scene Analysis – Seraji and Howard (2000), Talukhder et al. (2002), Huber et al. (1998), …**
- **Vehicle-Terrain Sensing**
  - **Wheels: Bekker (1969), Iagnemma et al. (2001), Yoshida & Hamano (2002), Iagnemma et al. (2003), …**
  - **Limbs: Hirose (1984), Espenschied et al. (1996), Wettergreen et al. (1995), Lewis & Bekey (2002), Kurazume & Zhang (1996), Raibert (1984), …**

Bounce Normalization

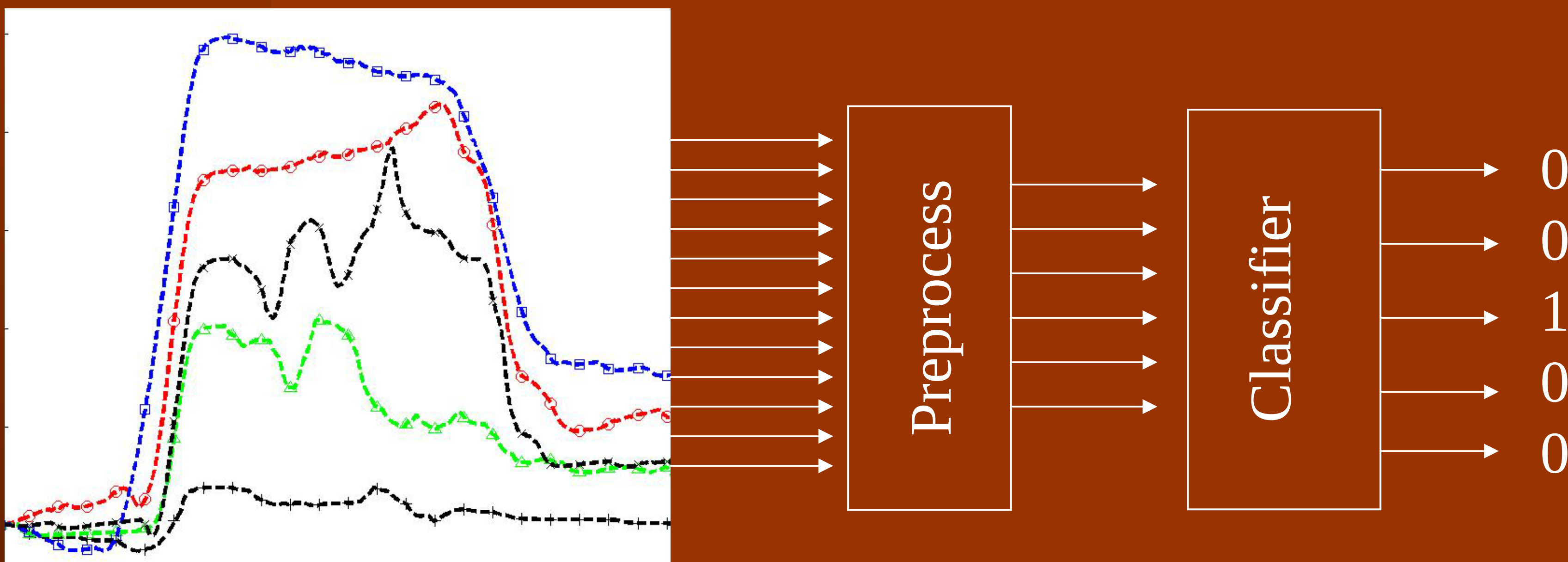
- Compensate for Body Roll Assuming Fixed Features
- Compensate for Perspective Distortion Assuming Linear





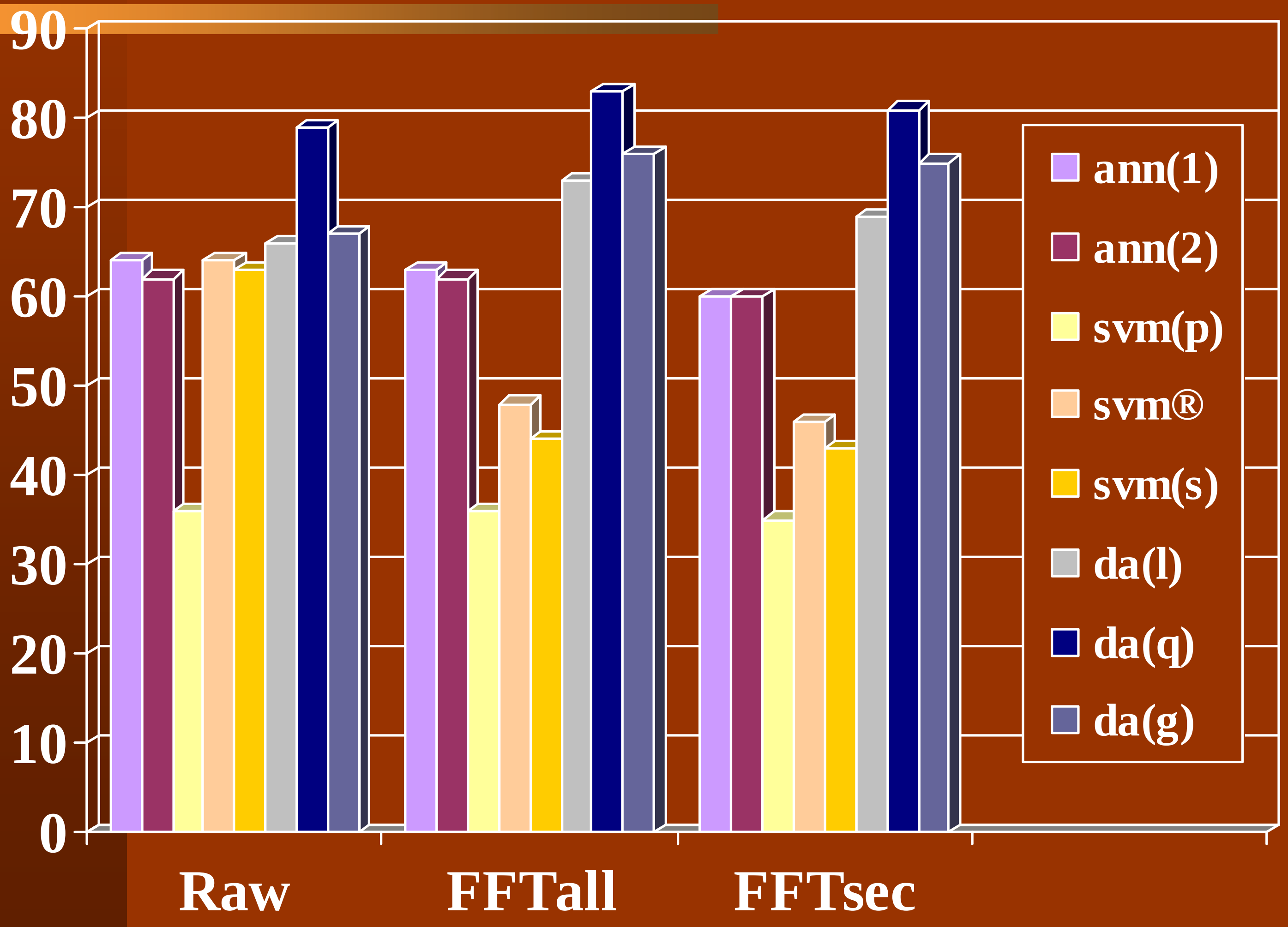


Terrain Classification
Using Spatial Discriminants



$f:\theta \longmapsto \mathbf{X}$ $\qquad$ $f:\mathbf{X} \longmapsto c$

Experimental Results – Raw Classifiers



Need for Adaptation

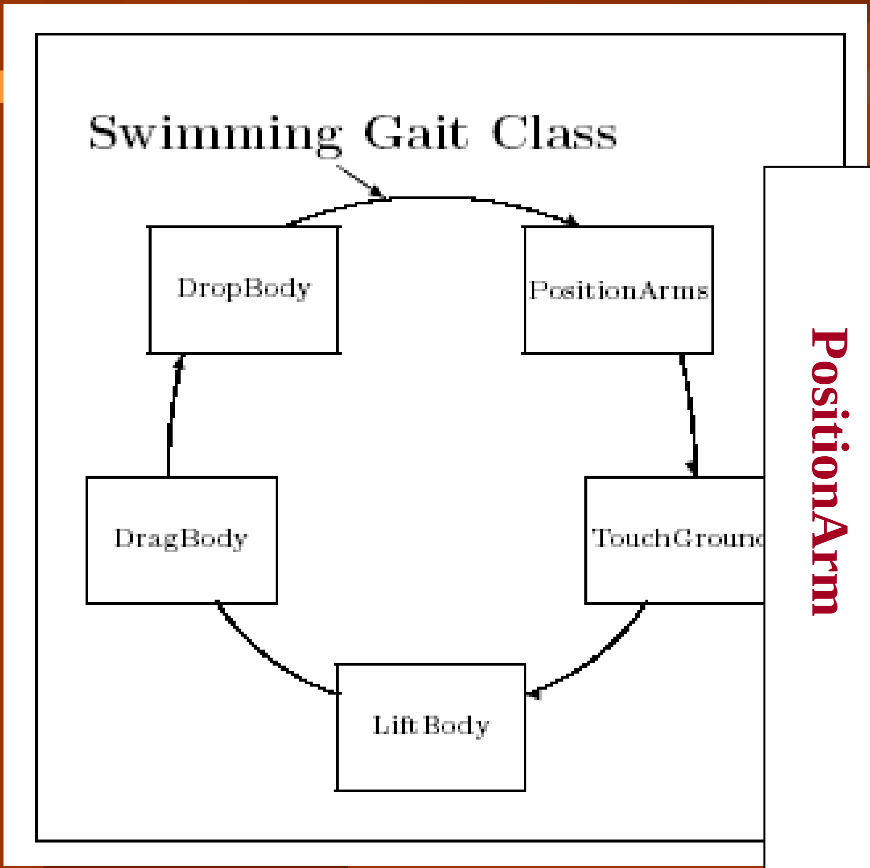
	Swim 1	Swim 2
Carpet	63.6	71.9
BBs	62.4	75.4
Foam	63.7	[illegible]

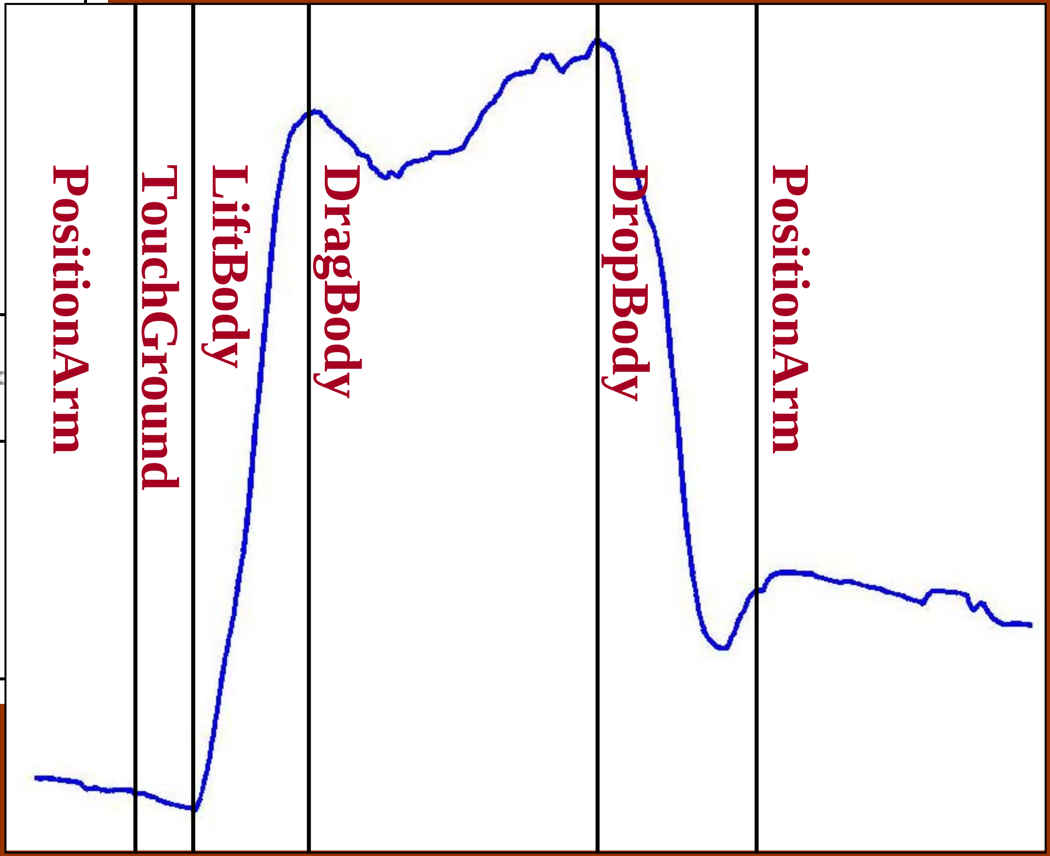
Energy (J)

Efficiency (J/cm)

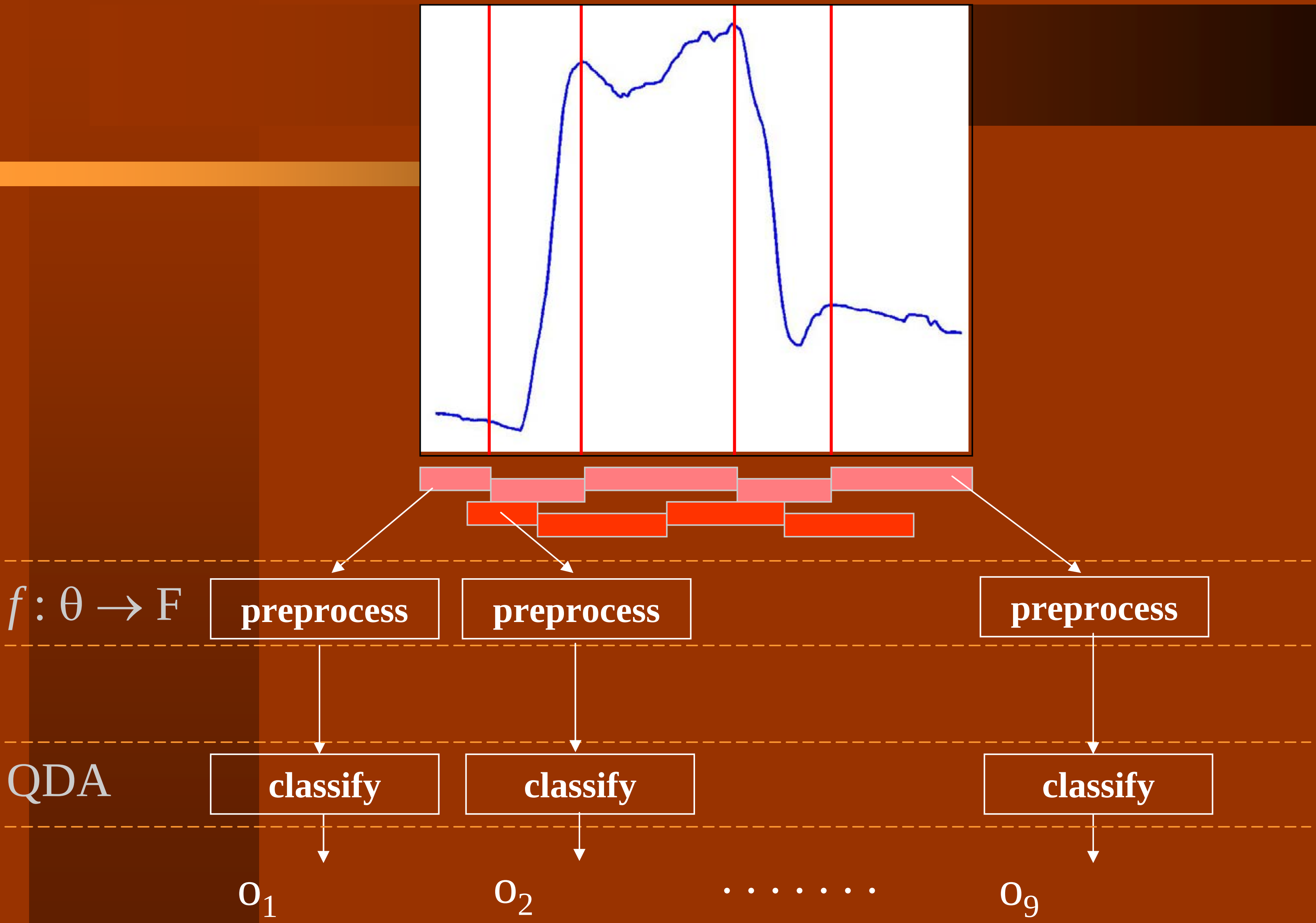
	Swim 1	Swim 2
Carpet	3.70	1.43
BBs	2.12	3.57
Foam	1.76	1.59

Active Sensing: Spatiotemporal Patterns and Gaits

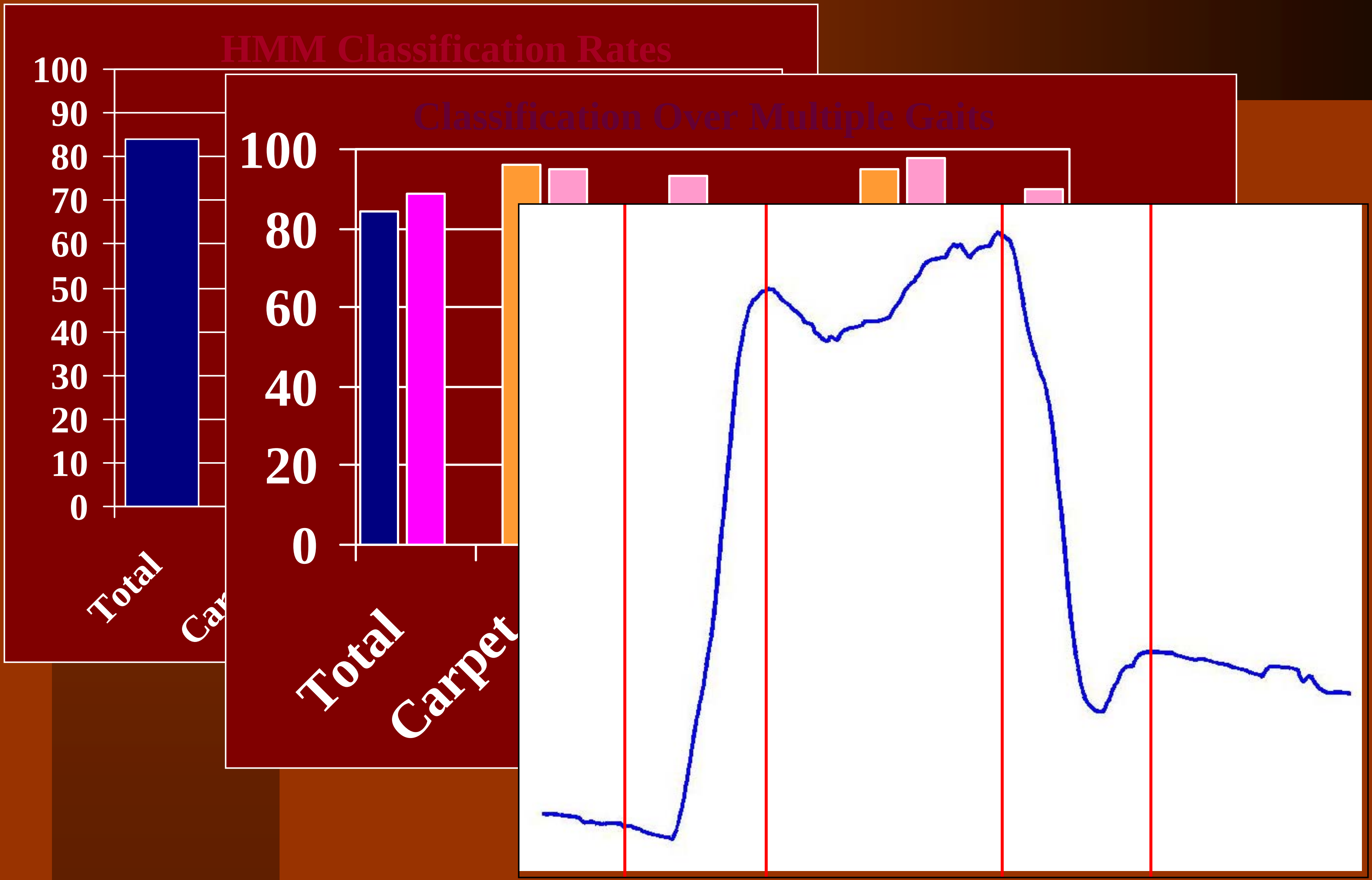




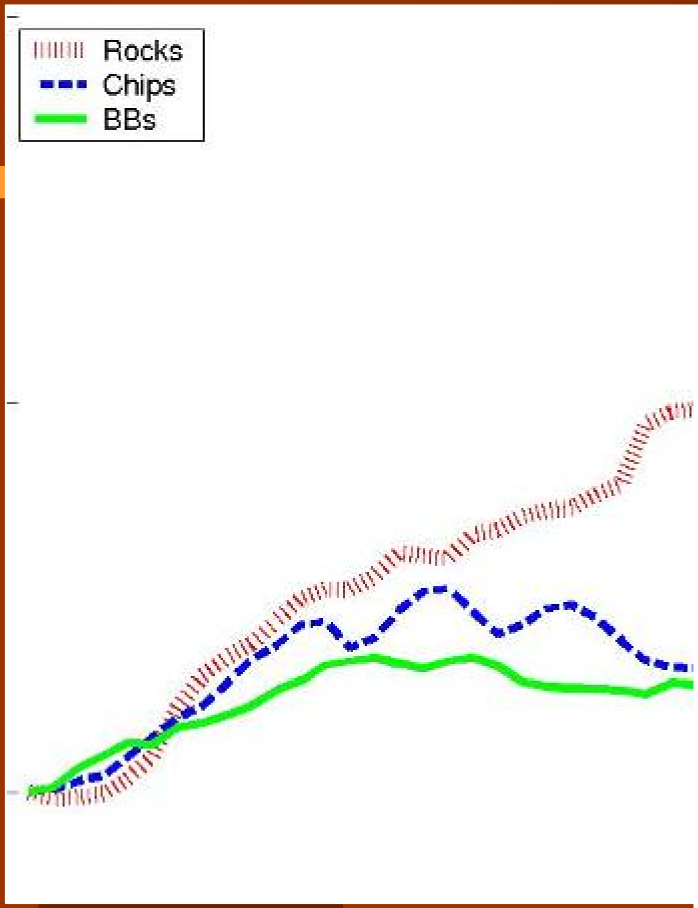
Observation Sequence

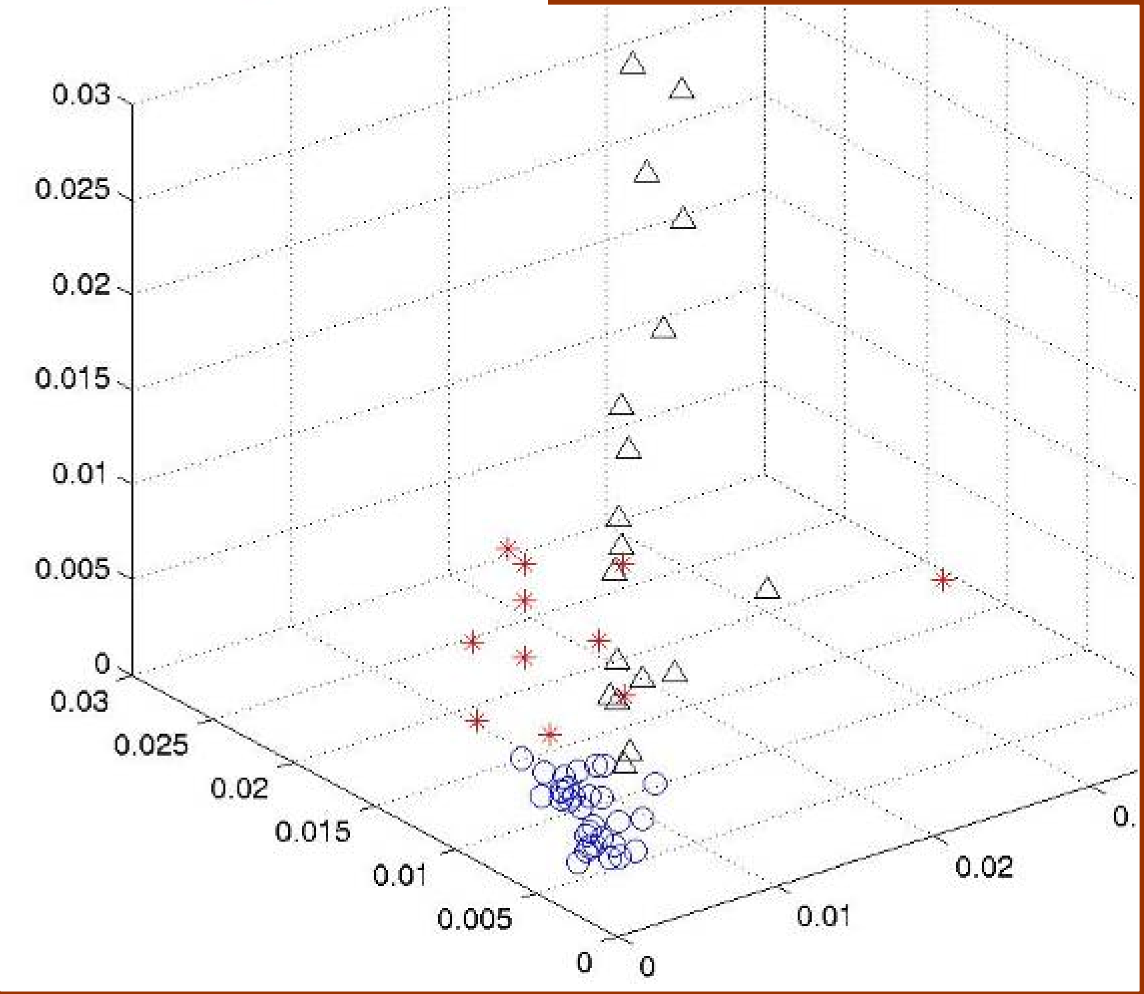


Experimental Results



General Applicability??





Treaded Vehicle

Evolving Gaits for Selectivity

- Adapting the gait based on local terrain improves vehicle performance
- Current terrain classification relies on variability in gait bounce across terrains.
- Can we evolve gaits to maximize variability (thus selectivity)?

Genetic Algorithm

- Encoding gaits (individuals).
  - Matrix of joint motion (1st row is initial position).
- Culling Agents
  - Remove unattainable joint positions
- Limb/Terrain Interaction Model
  - Estimate gait bounce
- Objective (Fitness) Functions
  - Guide genetic selection

Culling Agents

Gait Trajectory =

θ1	θ2	θ3
45	**36**	**-10**
+/-15	**+/-15**	**+/-15**
…	**…**	**…**

- If via results in culling condition, remove.
- If all via's removed, replace individual.

Culling Conditions

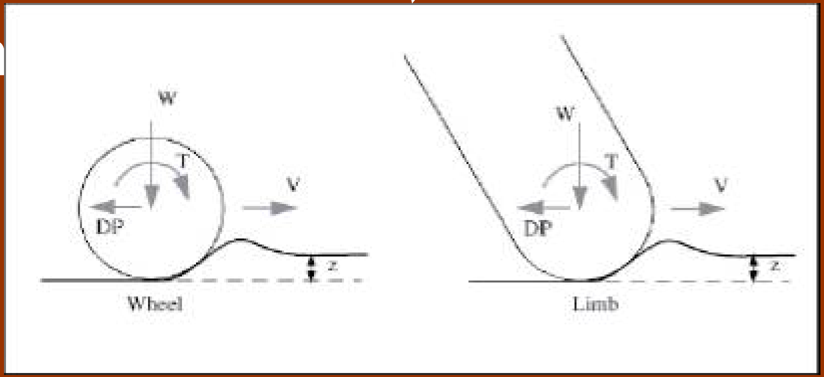
- **Fingertip or elbow inside the body**
- **Arms crossed**
- **Elbow motion moves forearm thru upperarm**
- **Joint limits exceeded**
- **Any portion of forearm inside body (not yet implemented)**

Limb/Terrain Interaction Model

Bekker's Wheel/Terrain Interaction Model

- **Estimates wheel sinkage (*s*)**
- **Uses load (*W*) on wheel**
- **Uses soil-specific coefficien**
  - **k_c : cohesion**
  - **k_φ : friction**
  - **n : exponent**

Interpreting TerminatorBot's fingertip as a wheel



$$S = [\ 3W\ /\ (3-n)(k_c + bk_\varphi)\mathrm{sqrt}(D)\ ]\ \hat{}\ (2/(2n+1))$$

Objective Functions

Maximize Distance

$$D = \sum_{(vias)} \alpha_i \cdot \alpha_{i-1} \,(\, y_{ft,i} - y_{ft,i-1} \,)$$

$\alpha_i = 1$ when limb in contact with ground.

$y_{ft,i}$: y-coord of fingertip at via *i*

Maximize Efficiency

$$E = \sum_{(vias)} .5(\neg\alpha_i+\neg\alpha_{i-1})\cdot(\theta_i - \theta_{i-1})\cdot e_n + .5(\alpha_i+\alpha_{i-1})\cdot(\theta_i - \theta_{i-1})\cdot e_c$$

e_n : energy/radian when not in contact with the ground

e_c : energy/radian when in contact with ground

Maximize Selectivity

$$\Delta b = \mathrm{sqrt}\,[\ \sum_{(freq)} (\, \mathrm{fft}(b_{t1})_I - \mathrm{fft}(b_{t2})_i \,)^2\ ]$$

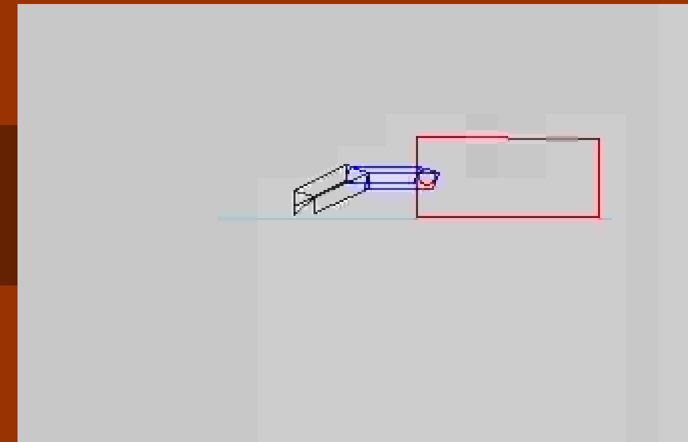
t_n : terrain *n*

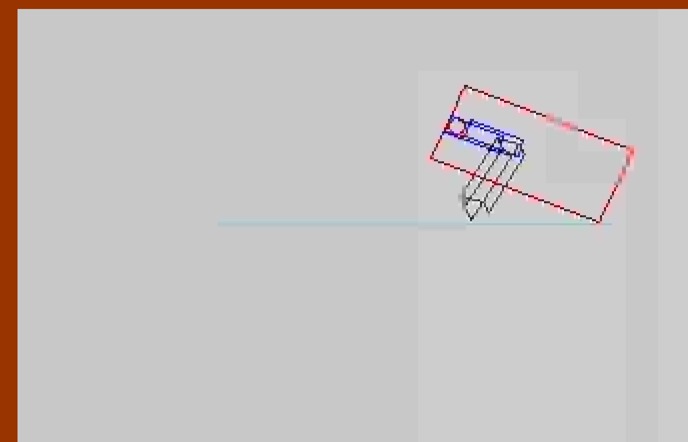
b_{tn} : bounce signature from traversing terrain t_n

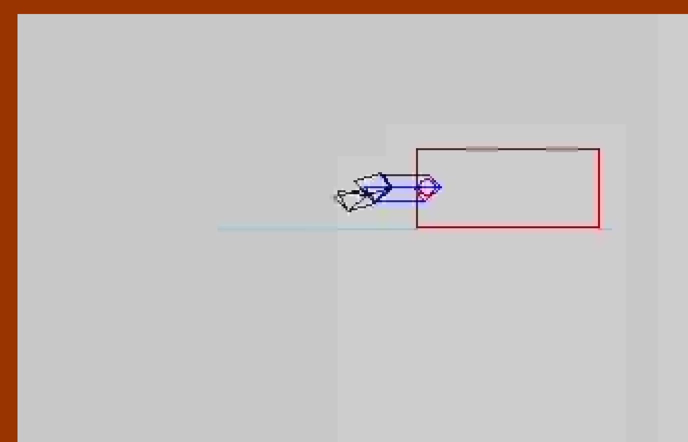
(obtained from limb/terrain model)

Evolved Gaits – Fitness Metrics

- **Efficiency**
- **Selectivity Only**
- **Distance & Selectivity**

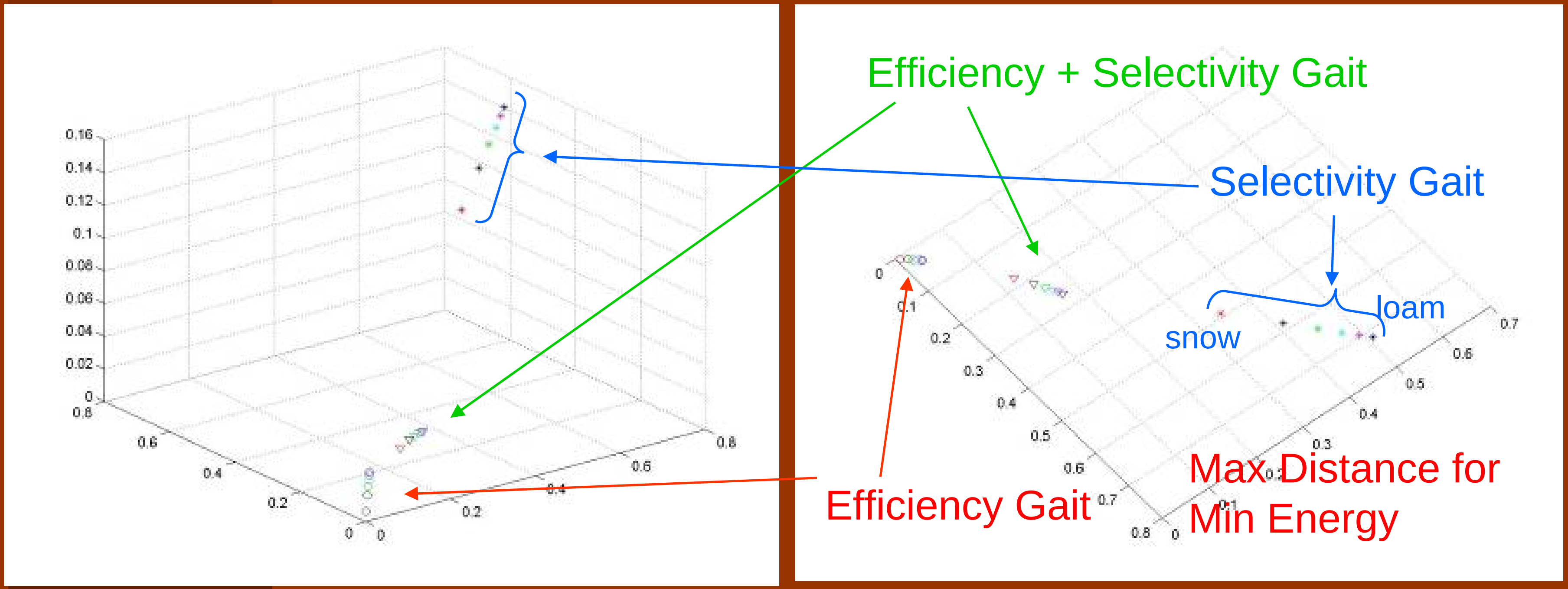




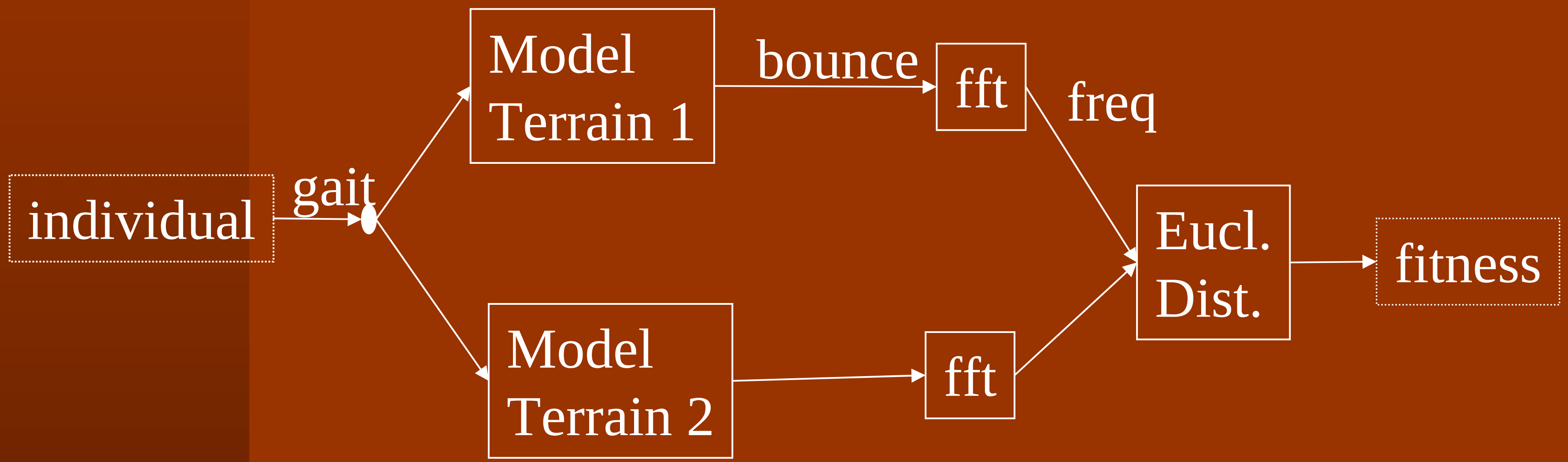


Clustering Results: Gaits on Terrains

- **Simulated, Pre-processed Gait Bounce Signature ("cluster space")**



Selectivity Fitness

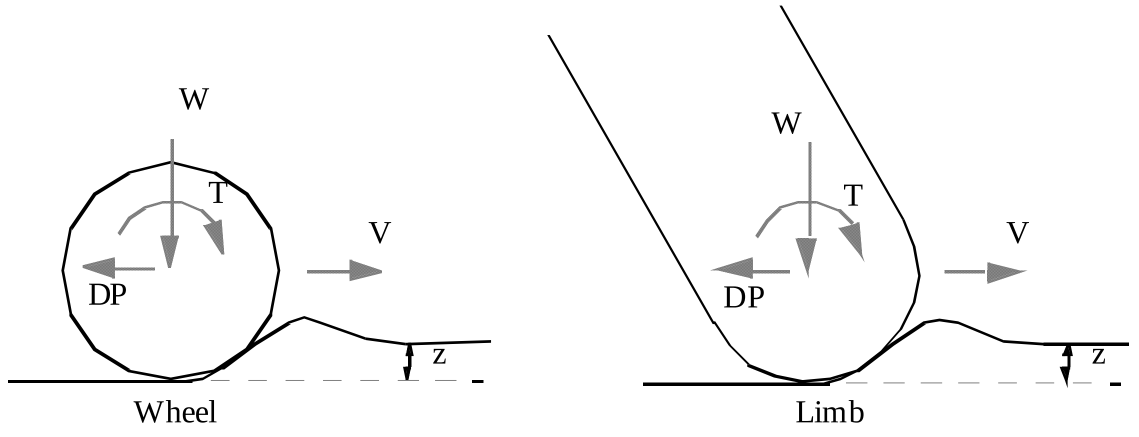


Summary

- Terrain Classification from V Servo Error
  - Gait Bounce metric
  - No Additional Sensors
  - ~90% recognition accuracy over 5 terrain samples (~700 trials)
  - “Somewhat” applicable to general vehicles
- Preliminary work on gait evolution for classification selectivity

Core-Bore CRAWLER Video

shown faster than real time


W
T
V
DP
z
Wheel
W
T
V
DP
z
Limb

Energy Efficient Reconnaissance using a Rotational Legged Locomotion Platform

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ARL Workshop on Mobility, Needham MA, Oct 5th 2006.

Rotational Legged Locomotion*

**** Funded by ARL STIR Grant P-49411-CI-II***

- Reconnaissance task
- Legs versus wheels
- Concept: Rotational Legged Locomotion
- Platform description
- Analysis of natural motion
- Motion Strategies
- Energy Efficiency
- Summary, Conclusions, Next Steps

Reconnaissance task

- Traverse a designated area with the objective of recording and reporting terrain and target features.
- Will encounter a wide range of terrain types
- May need to operate for long periods
- May need to evade pursuit

⇨Energy efficient, versatile locomotion

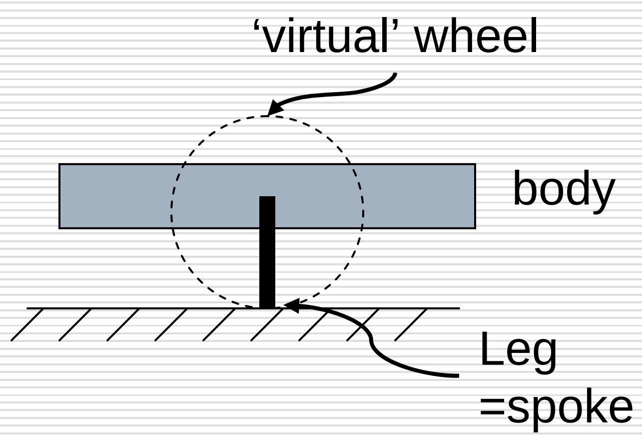
Legs versus Wheels

- Legs - versatile:
  - Can step over obstacles and into depressions
  - Need to lift as well as propel
- Wheels - efficient:
  - Need smoother terrain
  - Don't need to lift, just propel

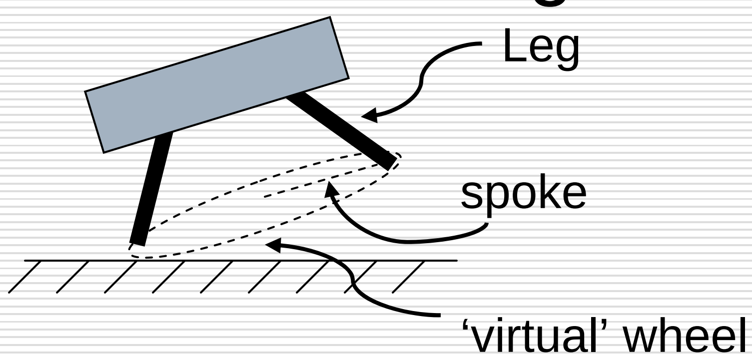
Rotopod Concept: Rotational Legged Locomotion

- Vertical wheel analog

e.g., [Altendorfer et al. 2001]
[Quinn et al. 2001]



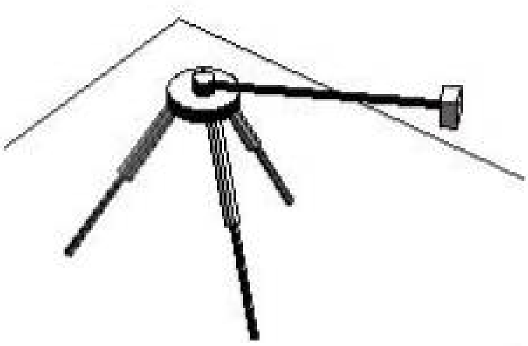
- Horizontal wheel analog



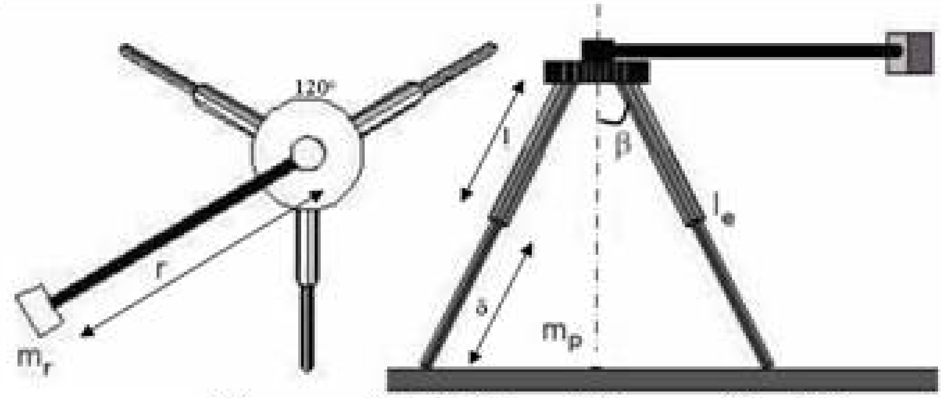
Design Approach

- Exploit the natural modes of motion of the mechanism

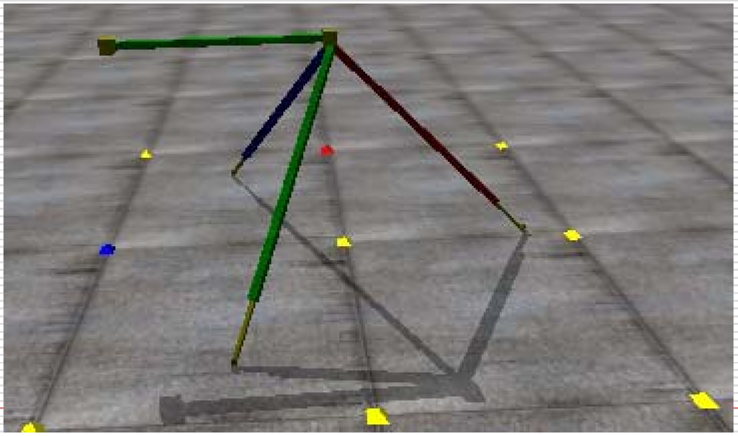
Platform Description



The Rotopod Mechanism



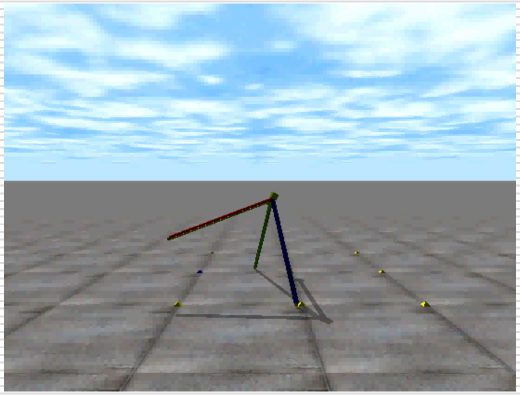
Rotopod. (a) Plan View (b) Side



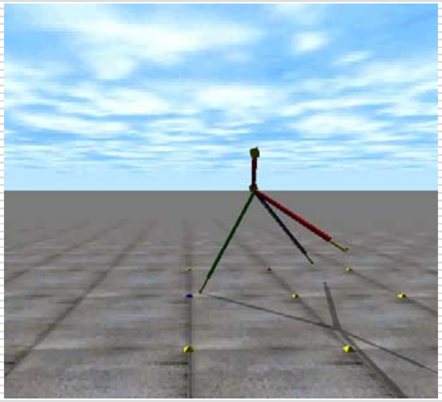
Open Dynamics Engine (ODE) Simulation

Locomotion

- Platform walks by rotating around leg endpoints



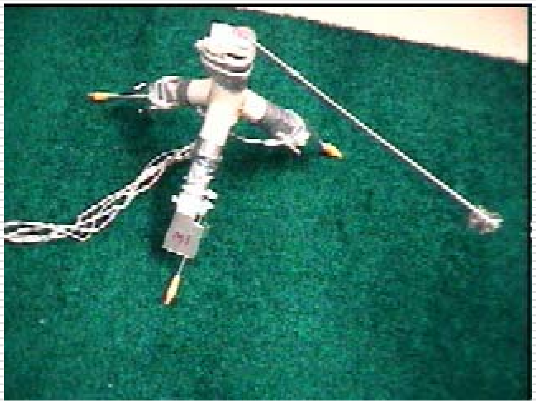
Slow



Fast

- Legs can 'step' over obstacle and depressions

Robot Platforms

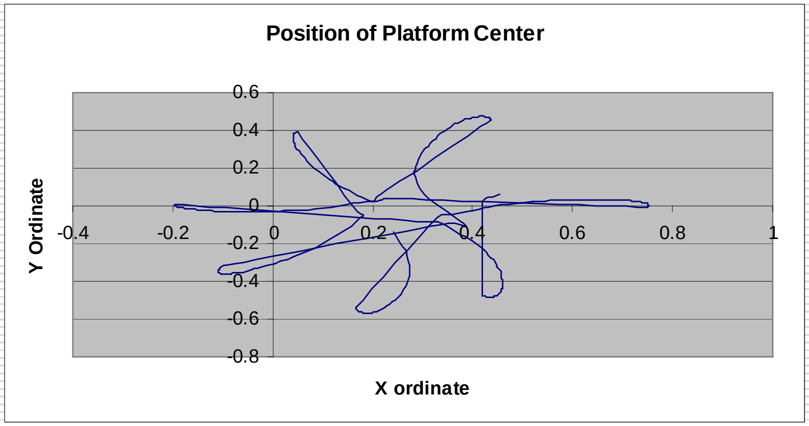


Version 1

Version 2

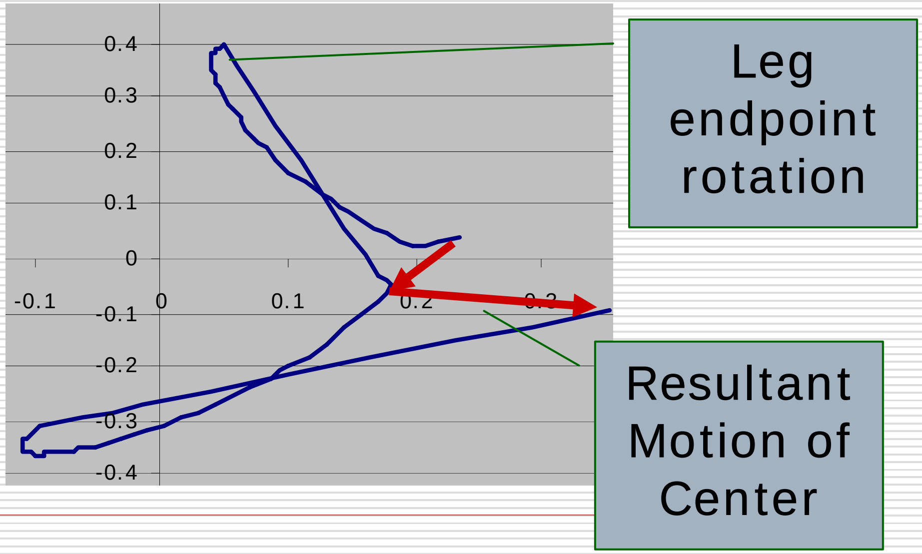
Natural Motion: Overview

- Overall trajectory is cycloidal



- Rotation around leg causes 'loop'

Reaction mass pulls and lifts as it approaches *opposition*, then pulls the other way as it leaves opposition

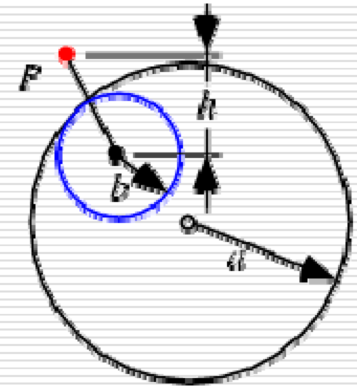


Natural Motion: Hypotrochoid

- Prolate Hypotrochoid

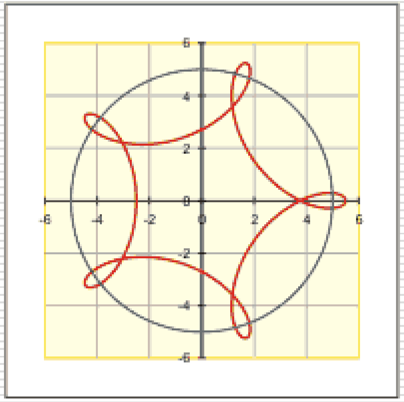
(has loops) (on the inside) (surface of a circle)

(1)

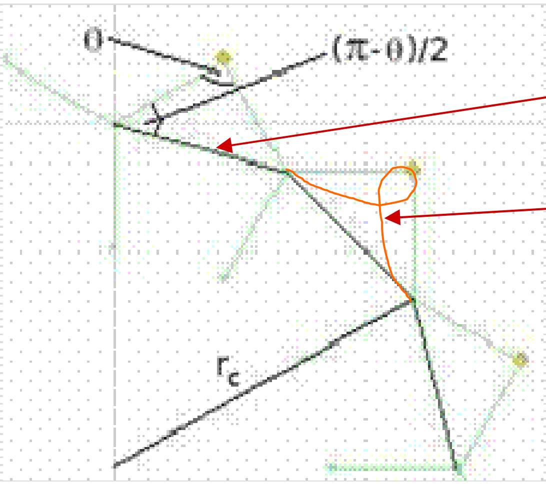


$$y = (a-b)\sin t - h\sin\left(\frac{a-b}{b}t\right),$$

$$x = (a-b)\cos t + h\cos\left(\frac{a-b}{b}t\right)$$



Natural Motion: Parameters



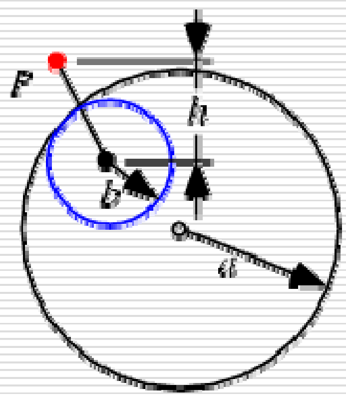
$$d(\theta) = 2l_e Sin\beta Sin\frac{\theta}{2}$$

Path of center

l_e =leg length

β = leg sep. angle

α = max tilt angle



$$r_c = a-(b+h)$$

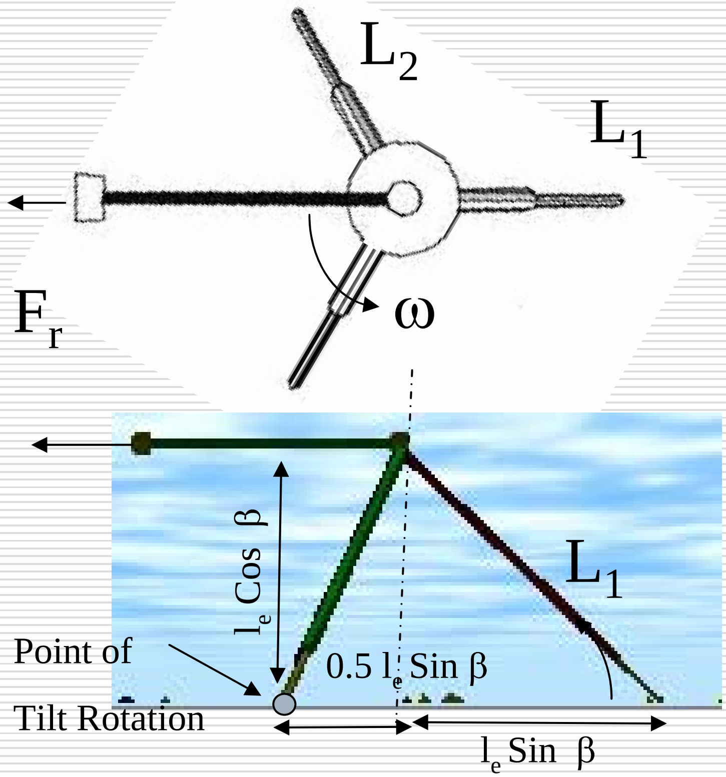
$$2\pi b = d(\theta) = 2l_e Sin\beta Sin\frac{\theta}{2}$$

$$a-(b-h) = l_e Sin\beta - l_e Sin(\beta+\alpha)$$

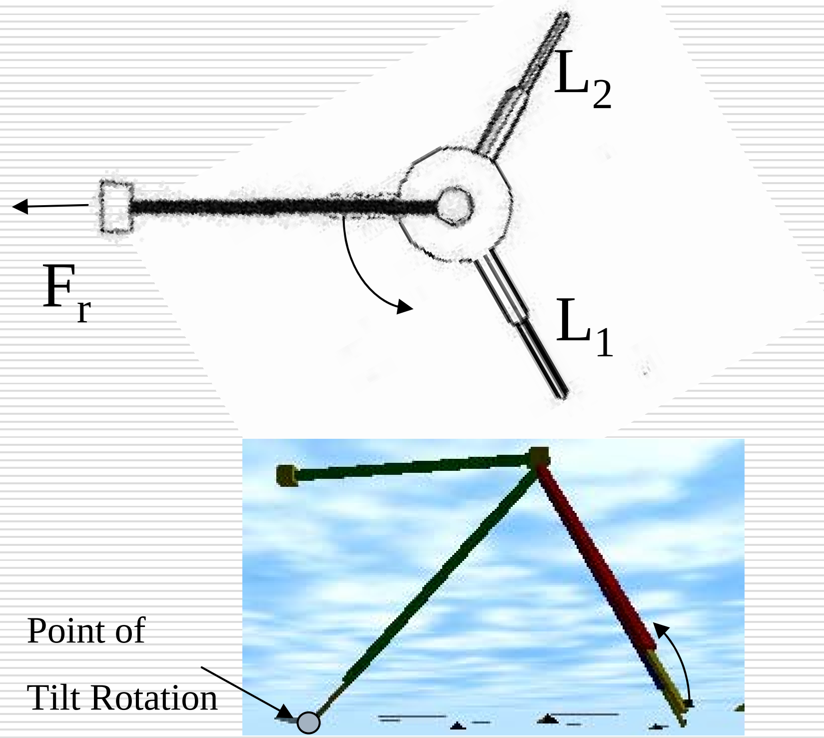
Natural Motion: Forces acting to tilt platform and raise leg

1. Single leg raise

$F_r = m_r \omega^2 r$



2. Two leg raise



Natural motion of platform:
Oscillatory Motion of Leg

- Rotating reaction mass causes leg to rise.
- Gravity causes the leg to fall.
- Three coupled oscillators: one per leg.

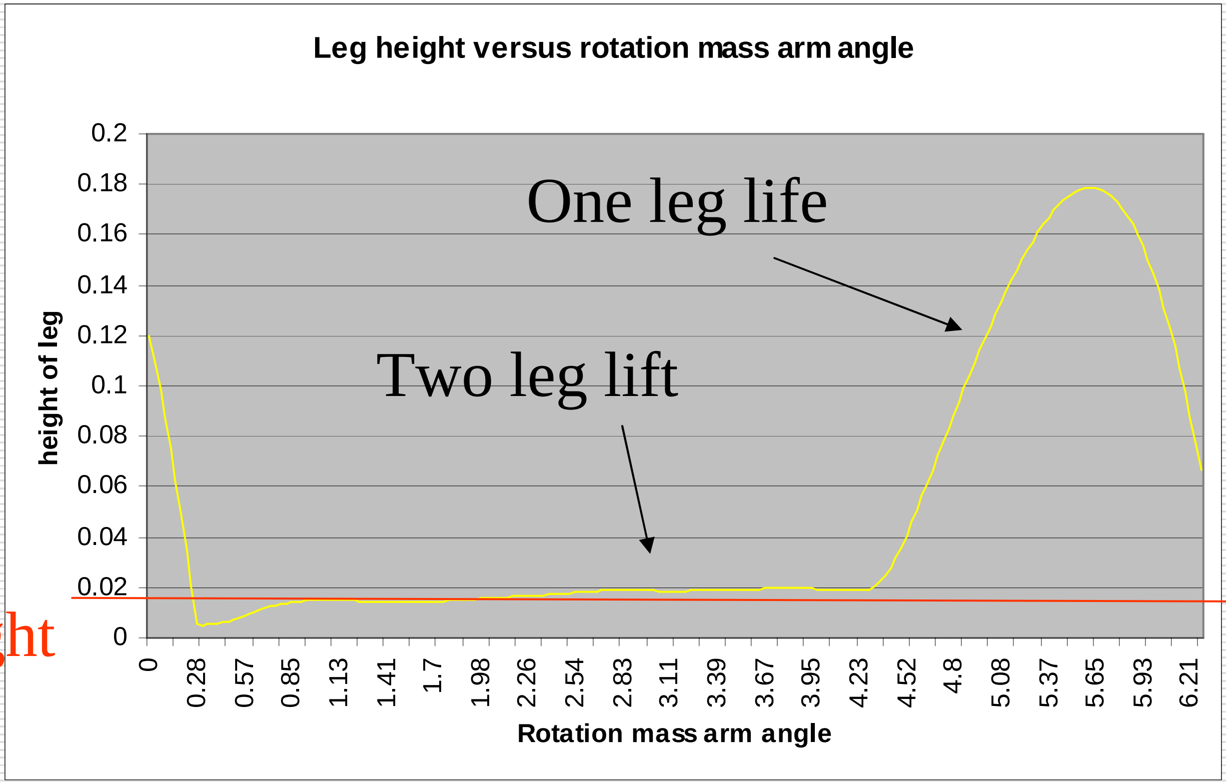
$$k_1 \ddot{z}_i + k_2 z_i = F_i Sin\theta$$

z_i is the z ordinate of the ith leg
k_1, k_2 constants of platform masses and lengths
F_i total force acting to raise leg i
θ reaction mass angle

Natural motion of platform:

Oscillatory motion of leg

$\theta_i = \pi / 3$



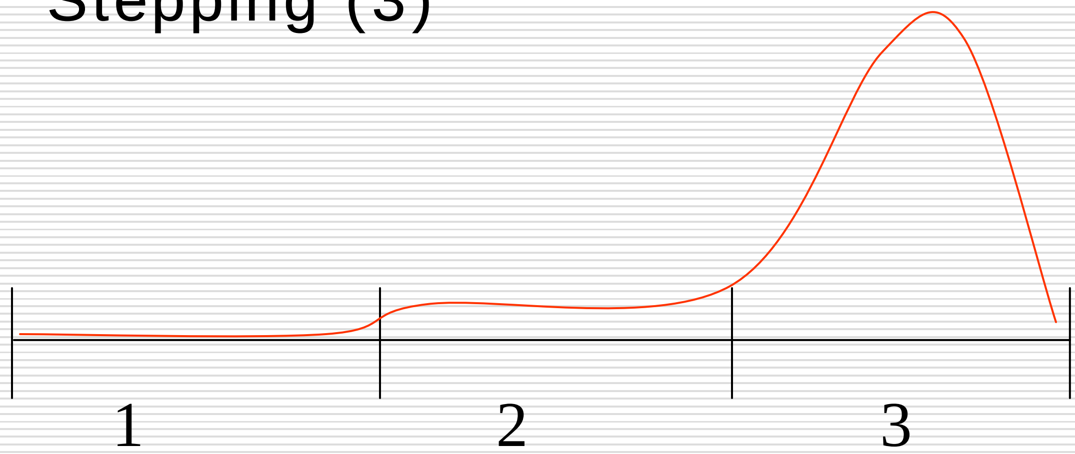
Resting height of leg

Open Dynamics Engine (ODE) simulation results

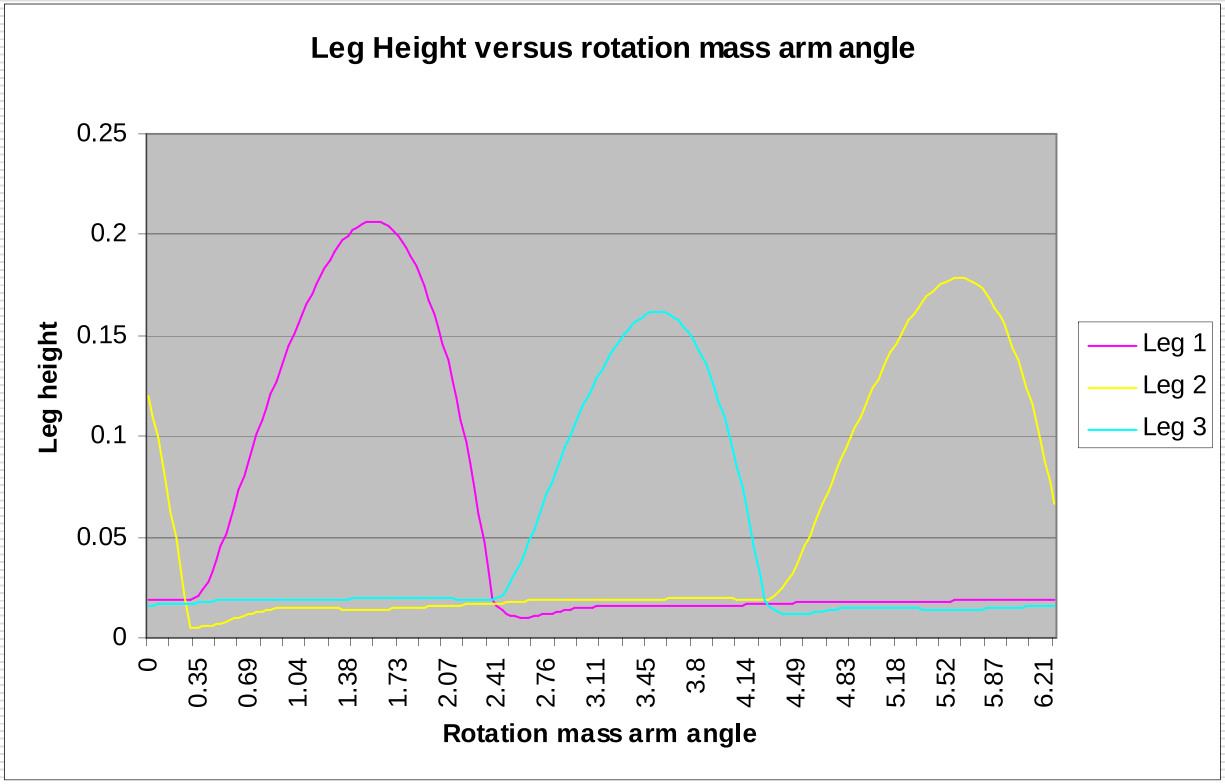
Natural motion of platform:

Phases of leg motion

- Leg height has three phases:
  - Resting (1)
  - Slipping (2)
  - Stepping (3)



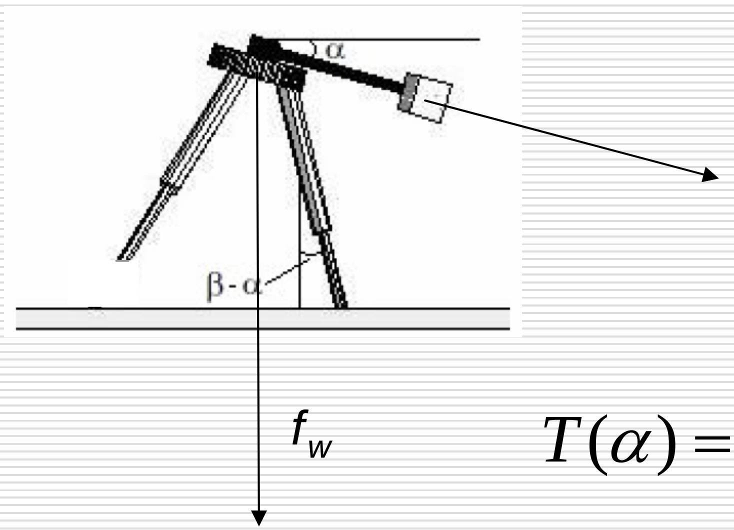
Natural motion of platform:
Three Coupled Oscillators



Open Dynamics Engine (ODE) simulation results

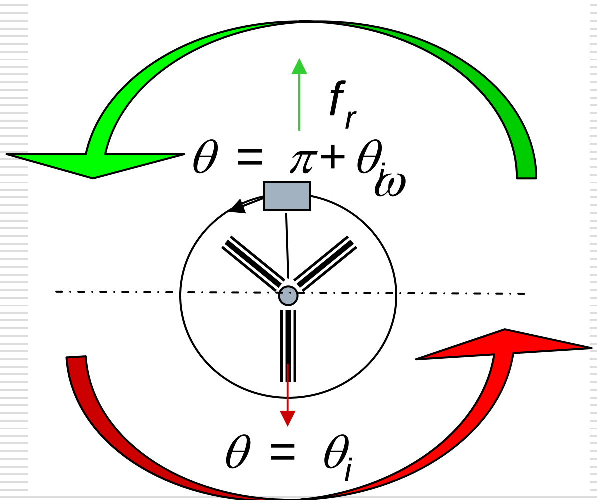
Natural motion of platform: Stability

- System will topple if a leg is raised beyond a critical angle = leg angle β.



$$T(\alpha) = f_w l_e Sin(\beta - \alpha) - f_r(\theta) l_e Cos\beta$$

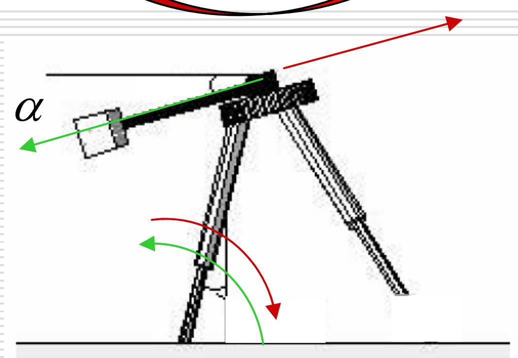
Natural Motion of platform: maximum tilt angle



Leg i height z_i peaks when $\theta = \theta_i - \pi/2$

$$T(\alpha) = f_w l_e Sin(\beta - \alpha) - f_r(\theta) l_e Cos\beta = m_P \ddot{\alpha}$$

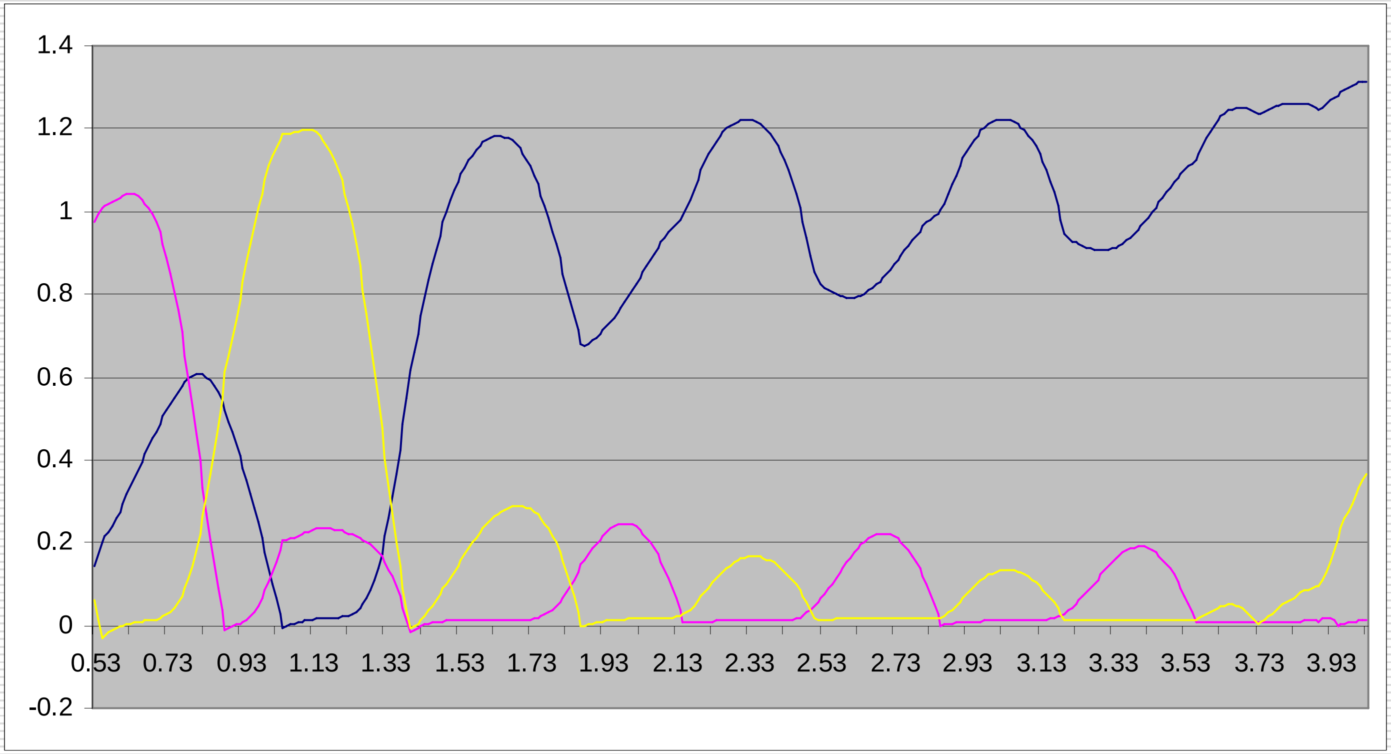
$$\alpha^* = \frac{1}{m_p} \int \int_{\theta_i - \frac{\pi}{2}}^{\theta_i + \frac{\pi}{2}} T(\alpha) d\theta$$



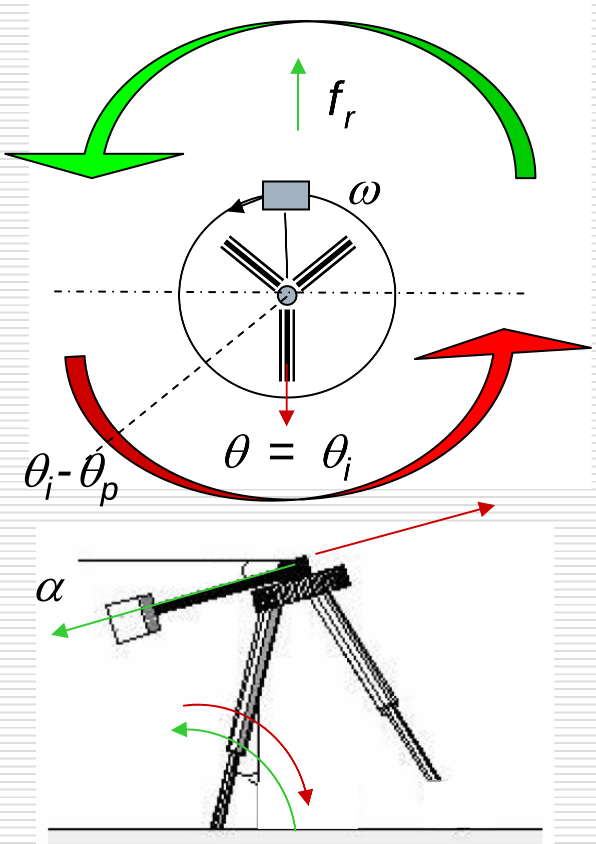
$$\alpha^* = \frac{1}{2}\left[\frac{l_e}{2m_p}[Sin(\beta) f_w - \sqrt{2} Cos(\beta) F_r]\right]\left[\frac{1}{2\omega}\right]^2$$

Unstable if $\alpha^* > \beta$

Natural Motion of Platform: Energy stored in leg



Natural Motion of platform: galloping instability



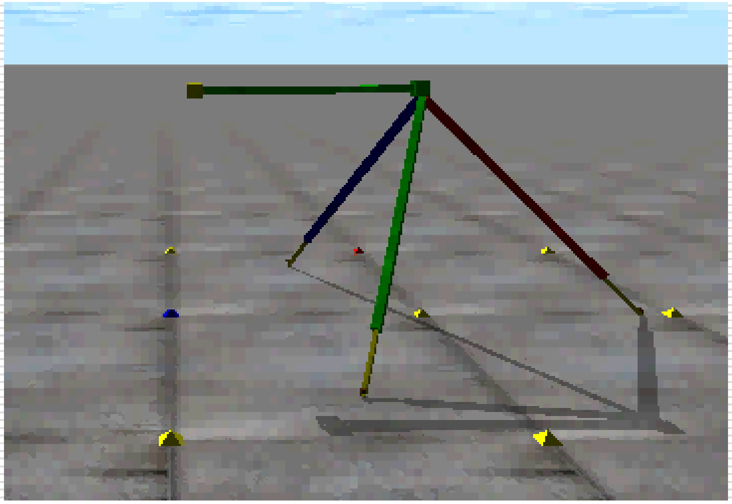
If leg i height z_i peaks at θ_i - θ_p > θ_i -$\pi/2$
For stability, z_i must go to 0 by $\theta = \theta_i + \pi/2$?

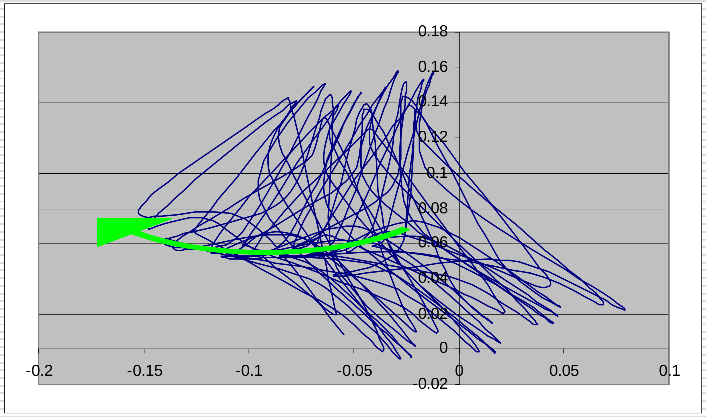
$$f_r = \frac{1}{\Theta} \int_{\theta_i - \theta_p}^{\theta_i + \pi/2} f_r(\theta) d\theta$$

$$\alpha^* > \frac{1}{2} \left[\frac{l_e}{2m_p} [Sin(\beta - 0.5\alpha^*) f_w + f_r] \right] \left[\frac{\Theta}{\omega} \right]^2$$

Motion Strategies: Leg Lengths

- Modify leg lengths to change motion, will rotate around platform center.

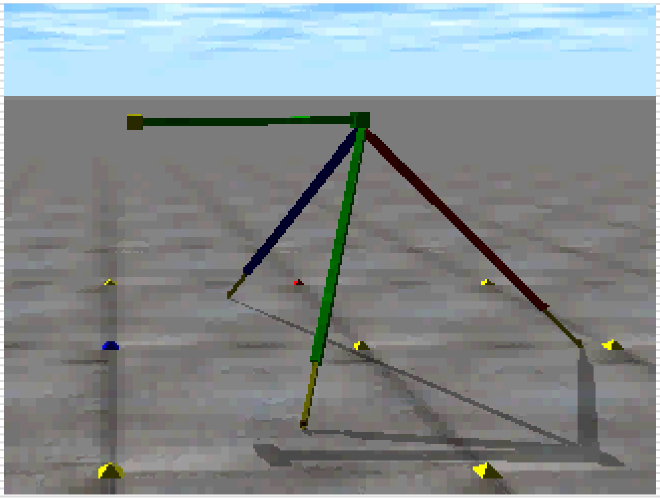


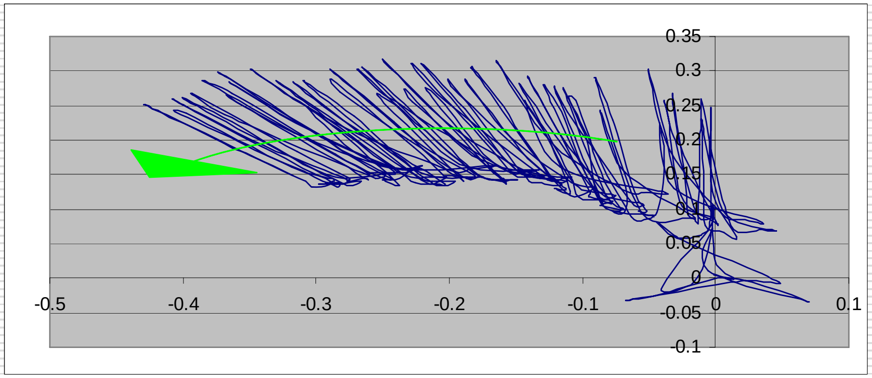


Slow, *negative* rotation around center.

Motion Strategies: Leg lengths and Rmass Velocity

- Rotate around leg endpoint

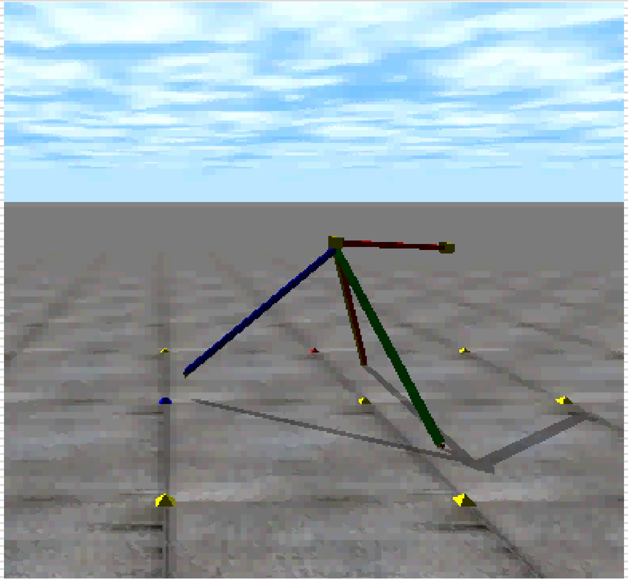


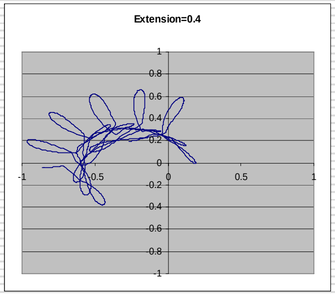


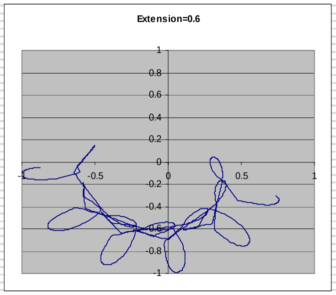
Faster, positive rotation around one or more Leg endpoint

Motion Strategies: Results of experimentation

- Varying leg selection & length

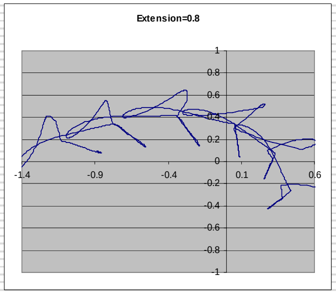






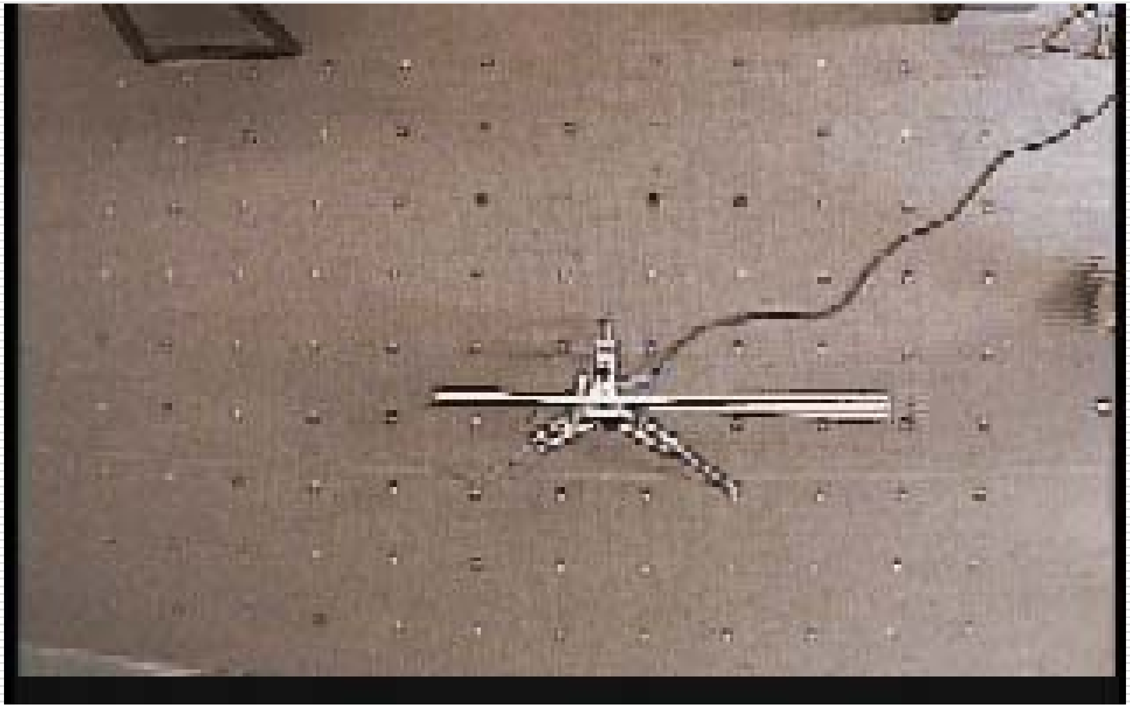
1 leg extended

Varying amounts



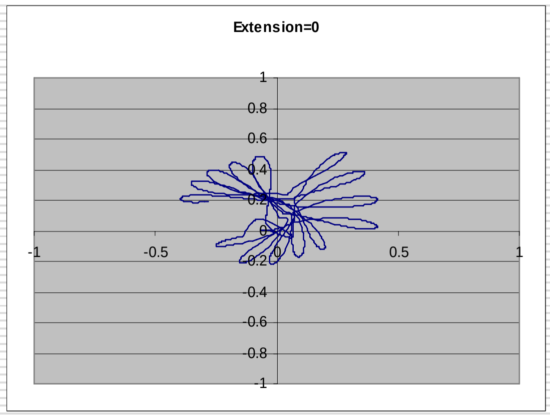
Motion Strategies

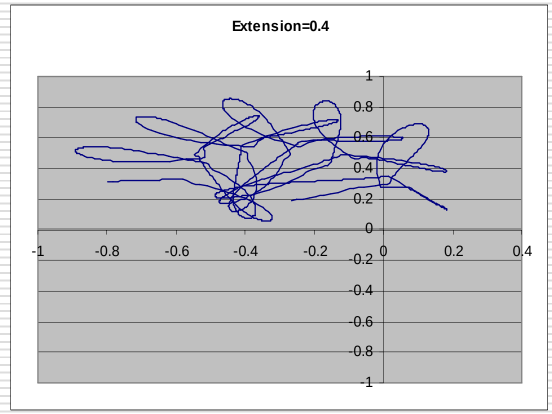
Movie: P2 Prototype Leg Phases Experiments

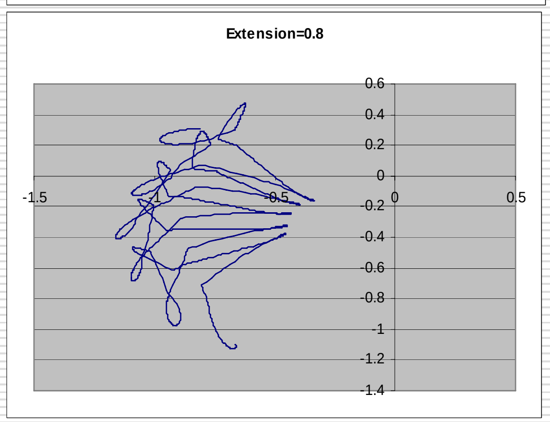


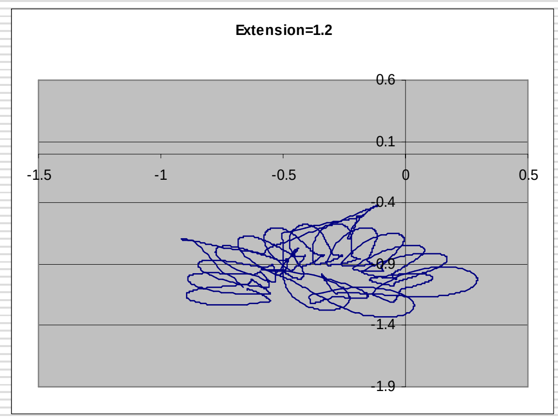
Motion Strategies: Results of experimentation

- 2 legs extended

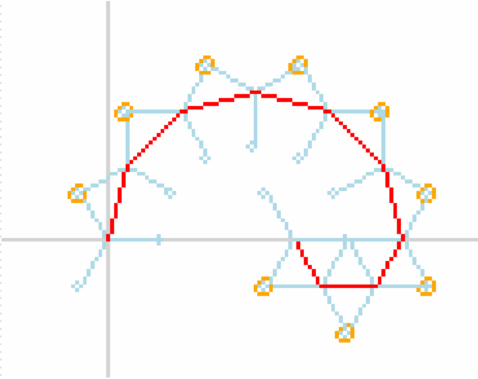






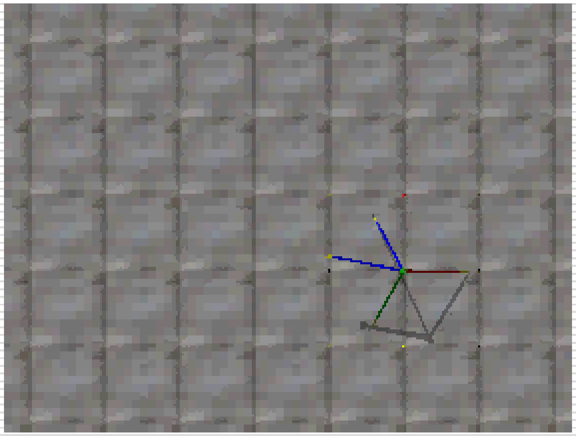


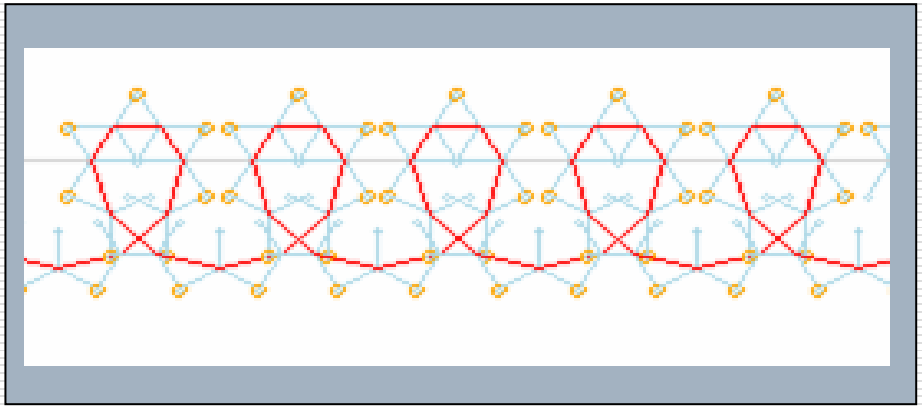
Motion Strategies: Cycloid Gait



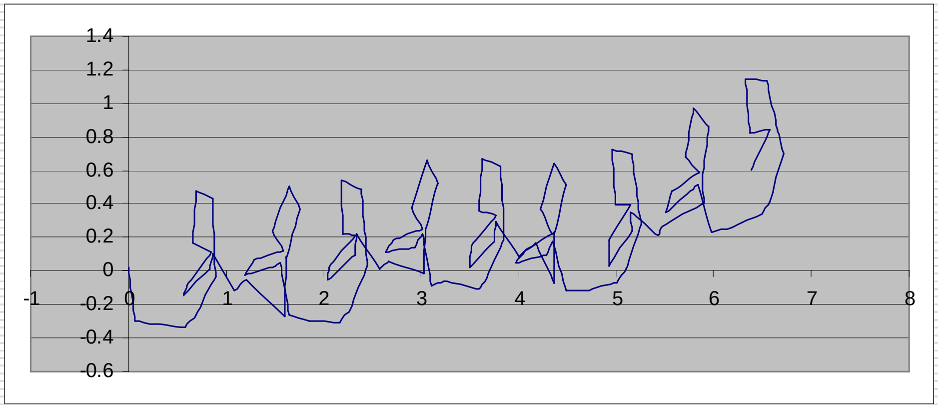
- Net forward motion given by difference of radii
- Easy to make corners – precision given by smaller radius
- Thickness of path covered given by sum of radii
- Recoverage of area given by ratio of radii

Motion Strategies: Cycloid Gait



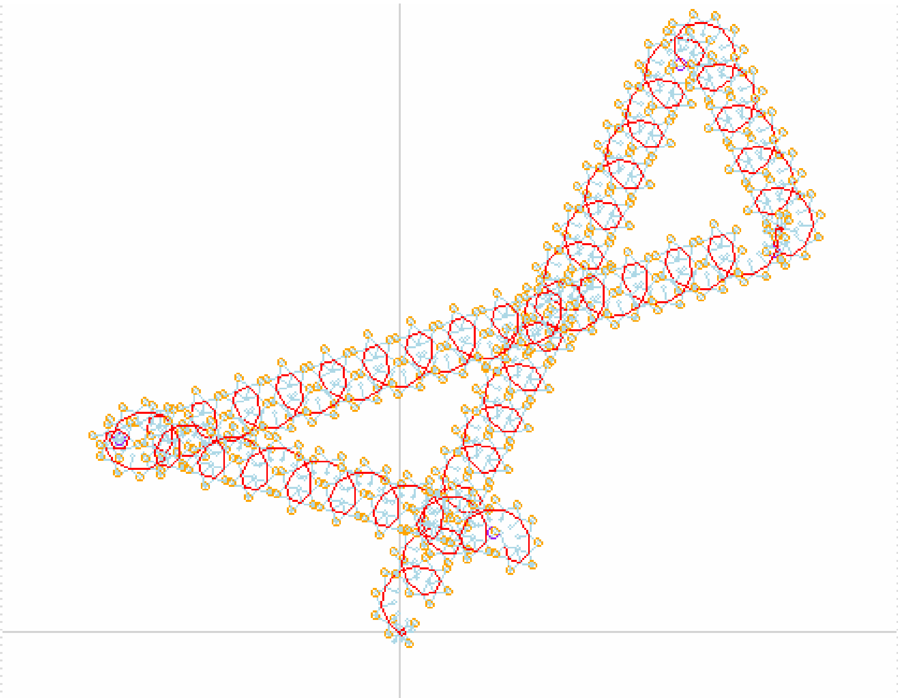


Kinematic simulation

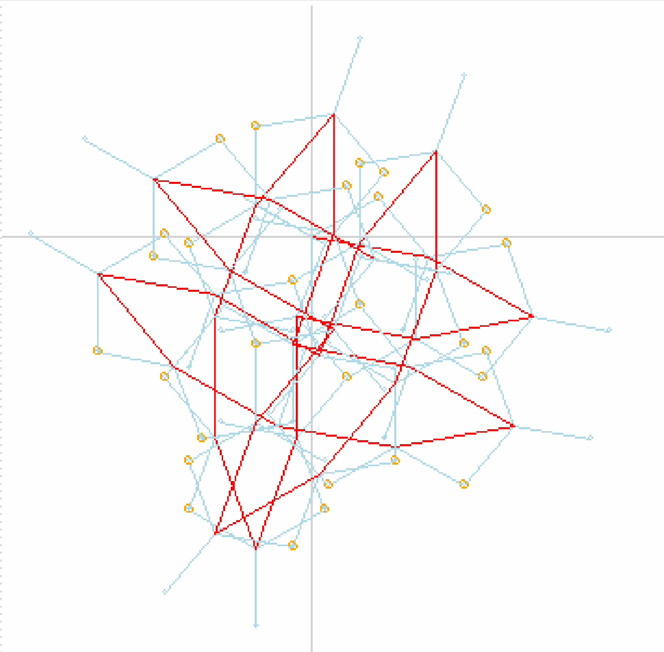


ODE simulation

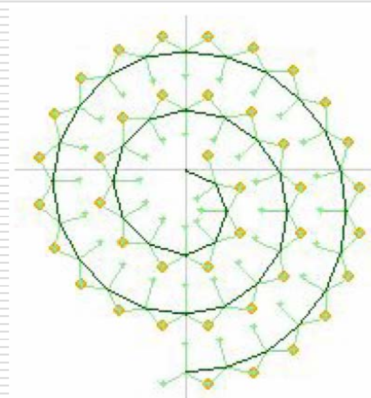
Motion Strategies: Cycloid gait path planning example



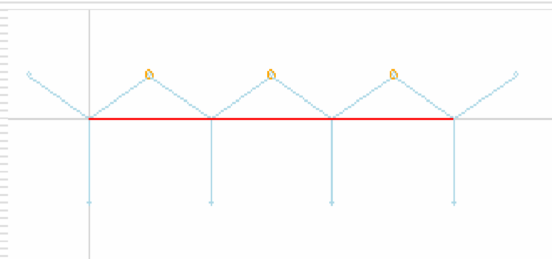
Motion Strategies: Other compound strategies



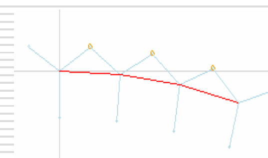
Area coverage:
(g1=[(L1,100)(L2,100)],
*g2=[(L2,100)(L3,100)])*x4

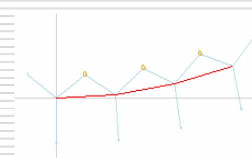


Spiral



Straight line



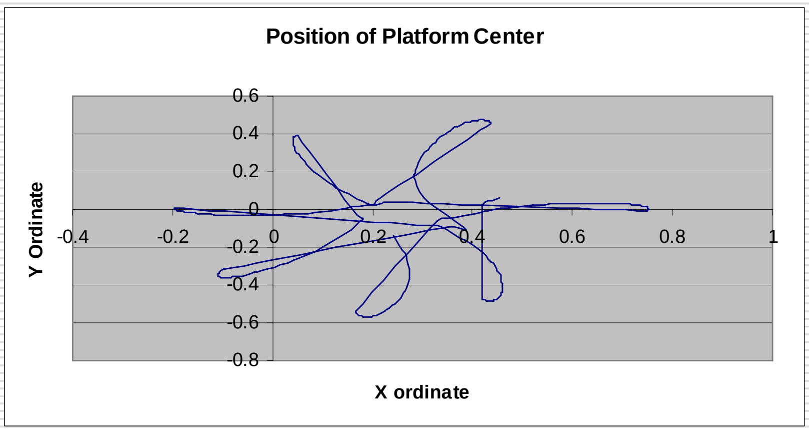


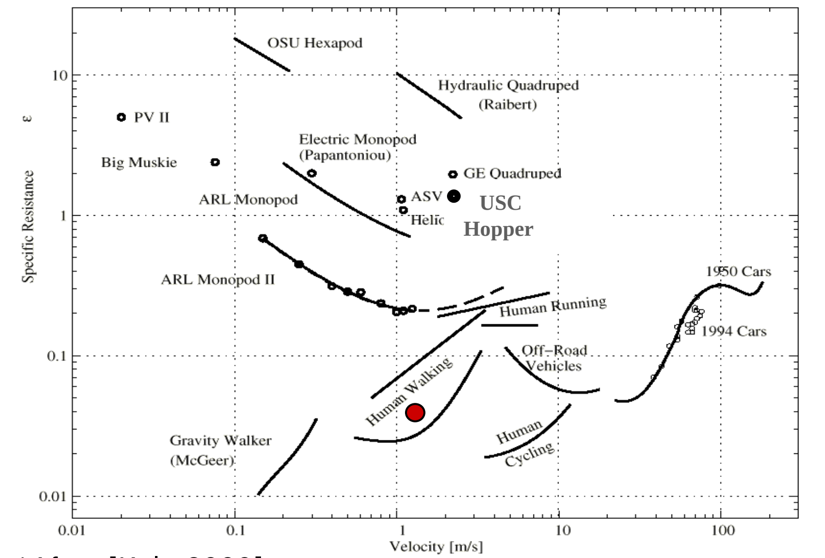
Energy Efficiency

- Specific Resistance
- Natural Motion

Specific Resistance

$$\varepsilon = \frac{power}{weight \times velocity}$$



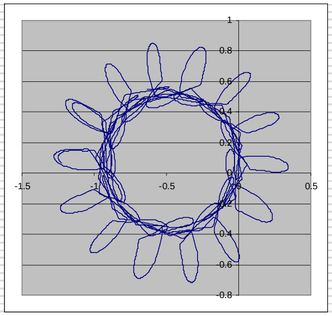


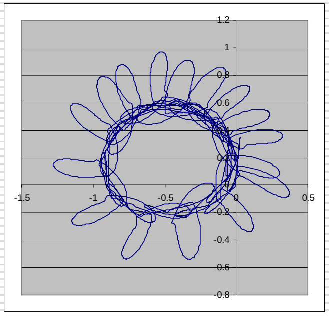
*After [Kale 2000]

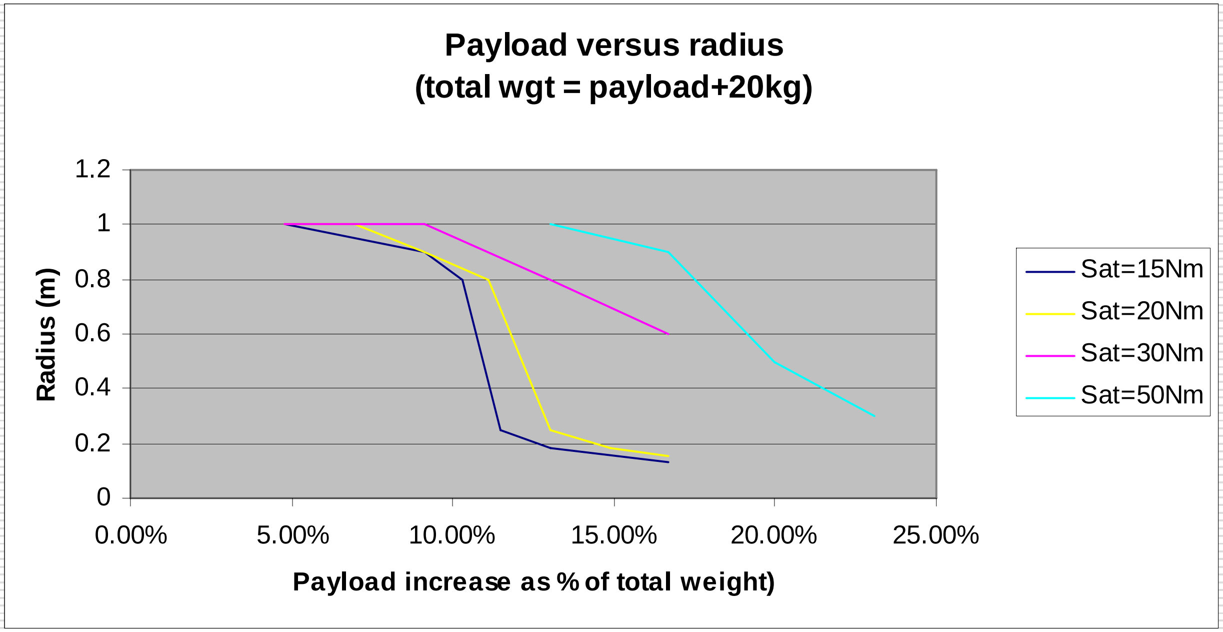
ODE Simulation:
ε =0.03 with
Center velocity 1.29 m/s

Energy Efficiency

- Limiting Reaction Mass Saturation Torque

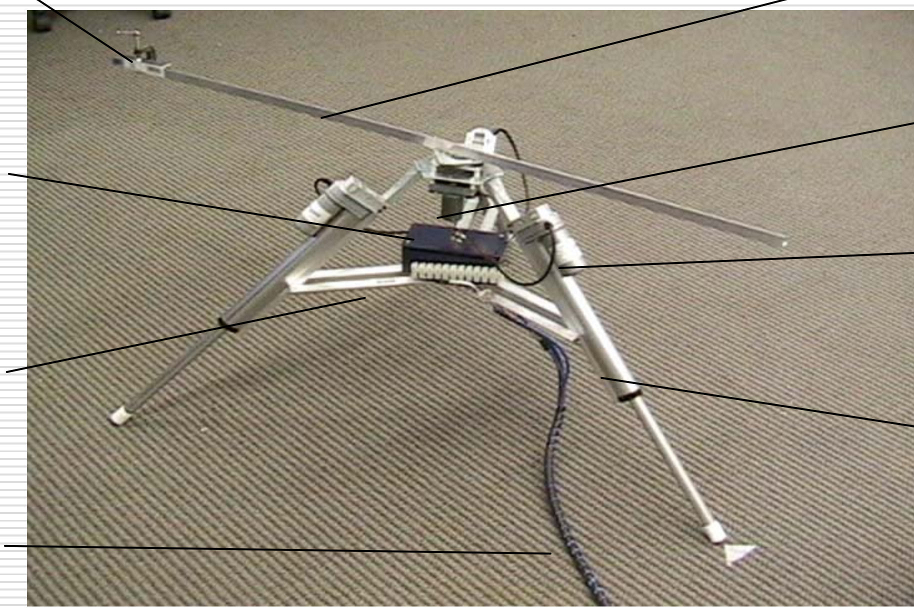






$$T(\alpha) = f_w l_e Sin(\beta - \alpha) - f_r(\theta) l_e Cos\beta$$

Platform: Second Prototype

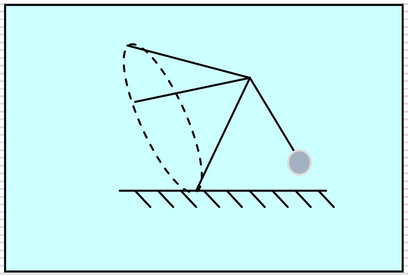


Summary

- Summary
  - **Platforms Built:**
    - Kinematic simulation (in python)
    - ODE simulation (in c)
    - Second prototype
  - **Feedforward motion strategies**
    - Motion along a curve
    - Compound gaits, esp. cycloid
  - **Energy efficiency**
    - Low energy natural motion
    - Effect of payload on energy use

Next Steps

- **Continuous motion strategies**
  - Rolling



- **Stepping over obstacles**
  - Controlling, selecting footfalls
- **Search patterns and metrics**
  - Energy-efficiency & coverage
- **Reconnaissance sensor deployment**
  - Rotating camera, laser scanners

Thank You

Team of Rotopods mapping an area

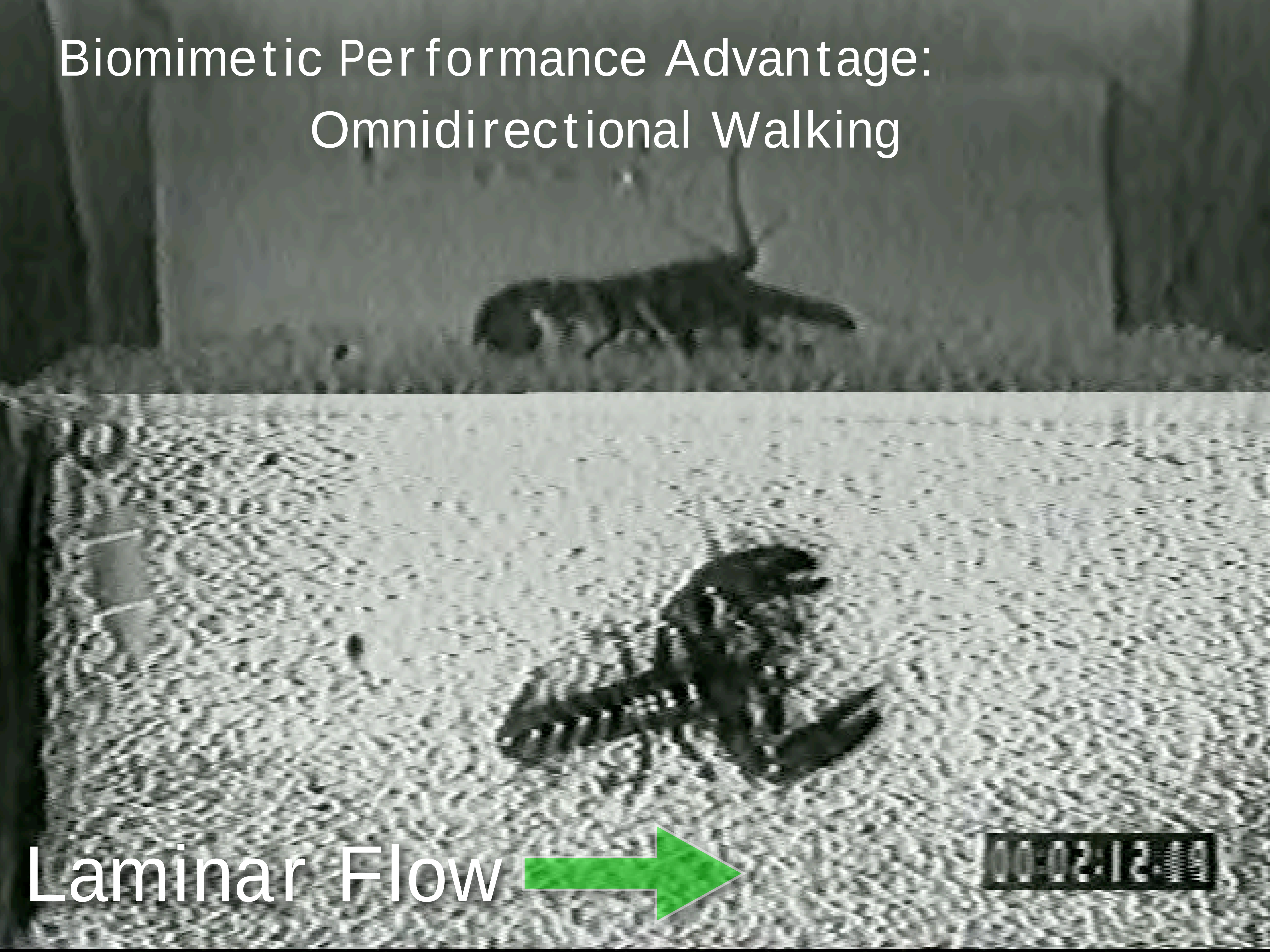
Controlling Biomimetic Robots with Electronic Nervous Systems

Joseph Ayers
Department of Biology and
Marine Science Center
Northeastern University
East Point
Nahant, Massachusetts
http://www.neurotechnology.neu.edu

Northeastern
UNIVERSITY

Biomimetics

- Let evolution do the design
- Identify performance advantages of the animal models
- Take advantage of proven behavioral strategies for autonomy
- Translate these capabilities to engineered devices


Biomimetic Performance Advantage:
Omnidirectional Walking
Laminar Flow

Northeastern University

RoboLobster

Fundamental Conundrum

Robots are Programmed: They get stuck
Animals wiggle and squirm out of tight spots

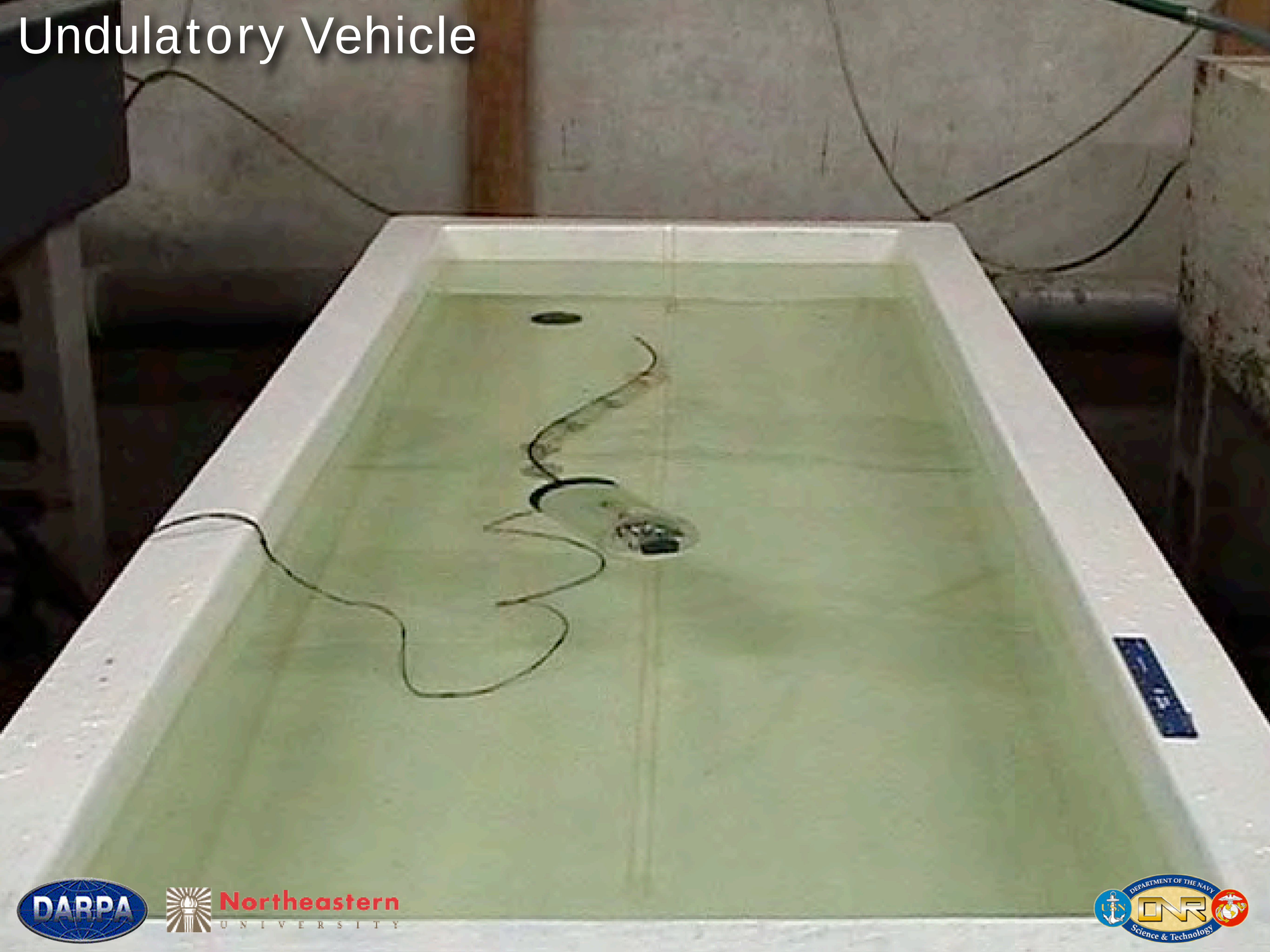
It is the basis of Autonomy

Solution: Control robots with electronic nervous systems that operate by similar mechanisms

DARPA

Department of the Navy ONR Science & Technology

Undulatory Vehicle



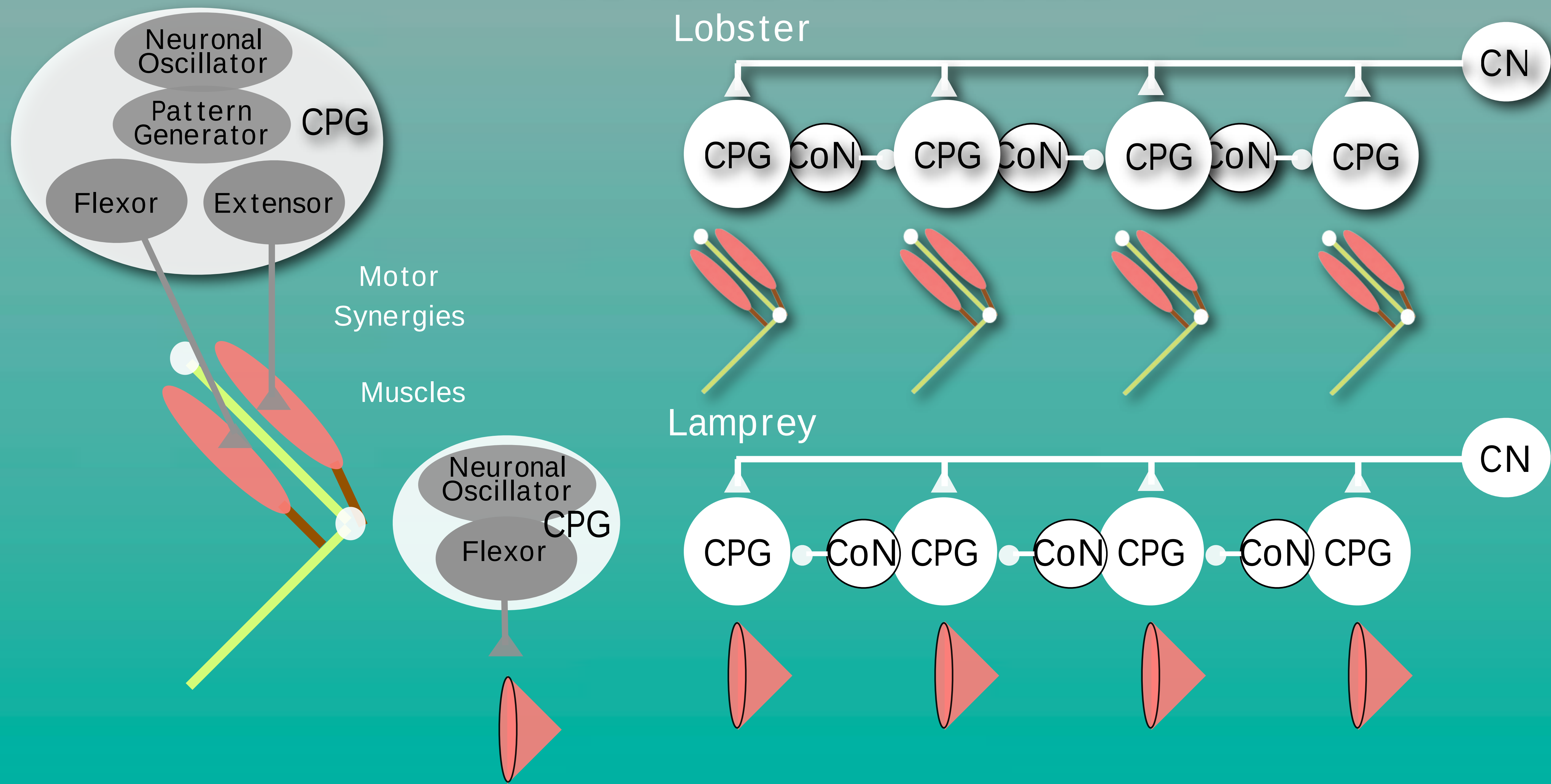
Neuronal Circuit-Based Controller

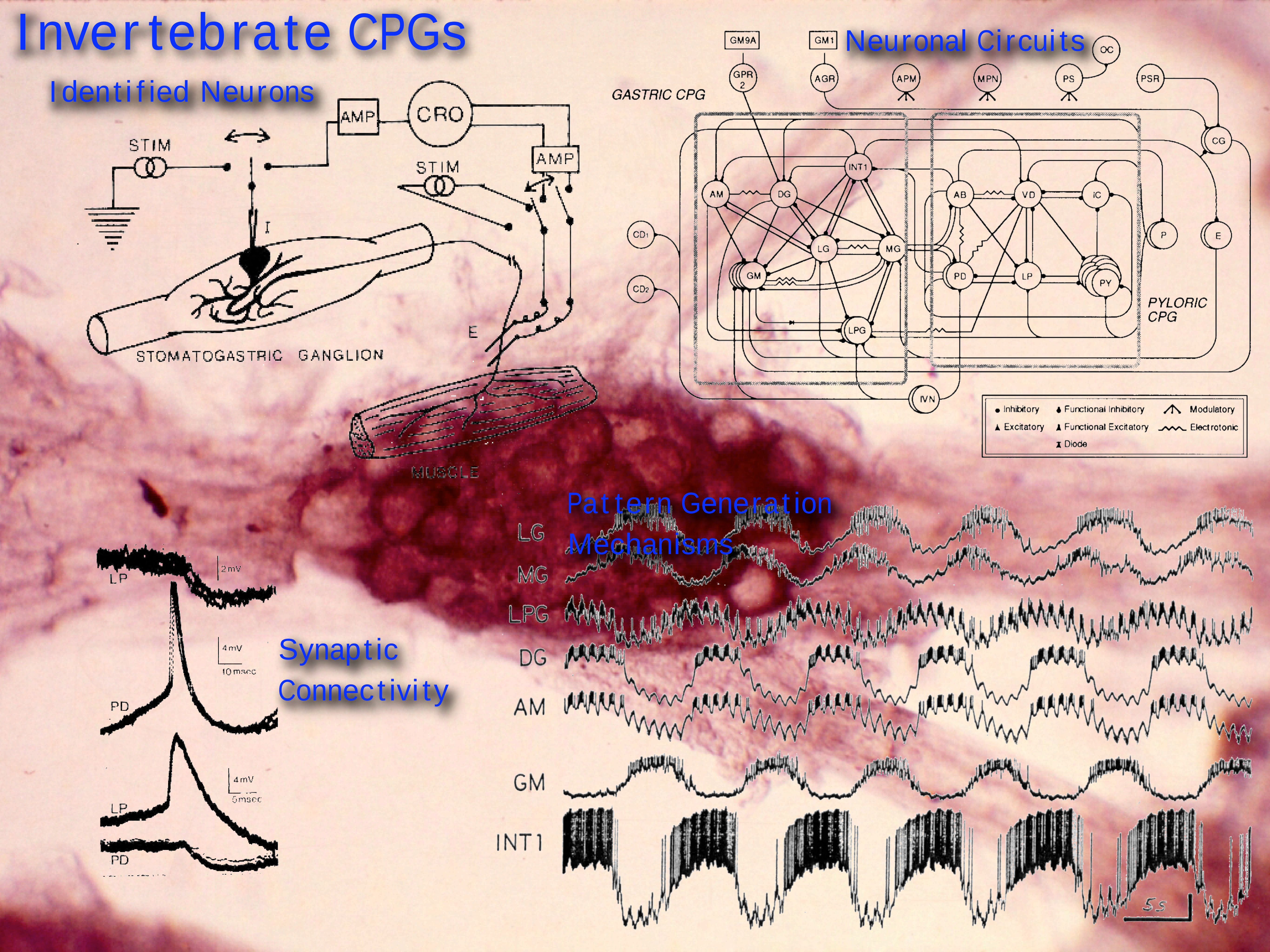
Based on Command Neuron, Coordinating Neuron, Central Pattern Generator Model

CN: Command Neurons

CoN: Coordinating Neurons

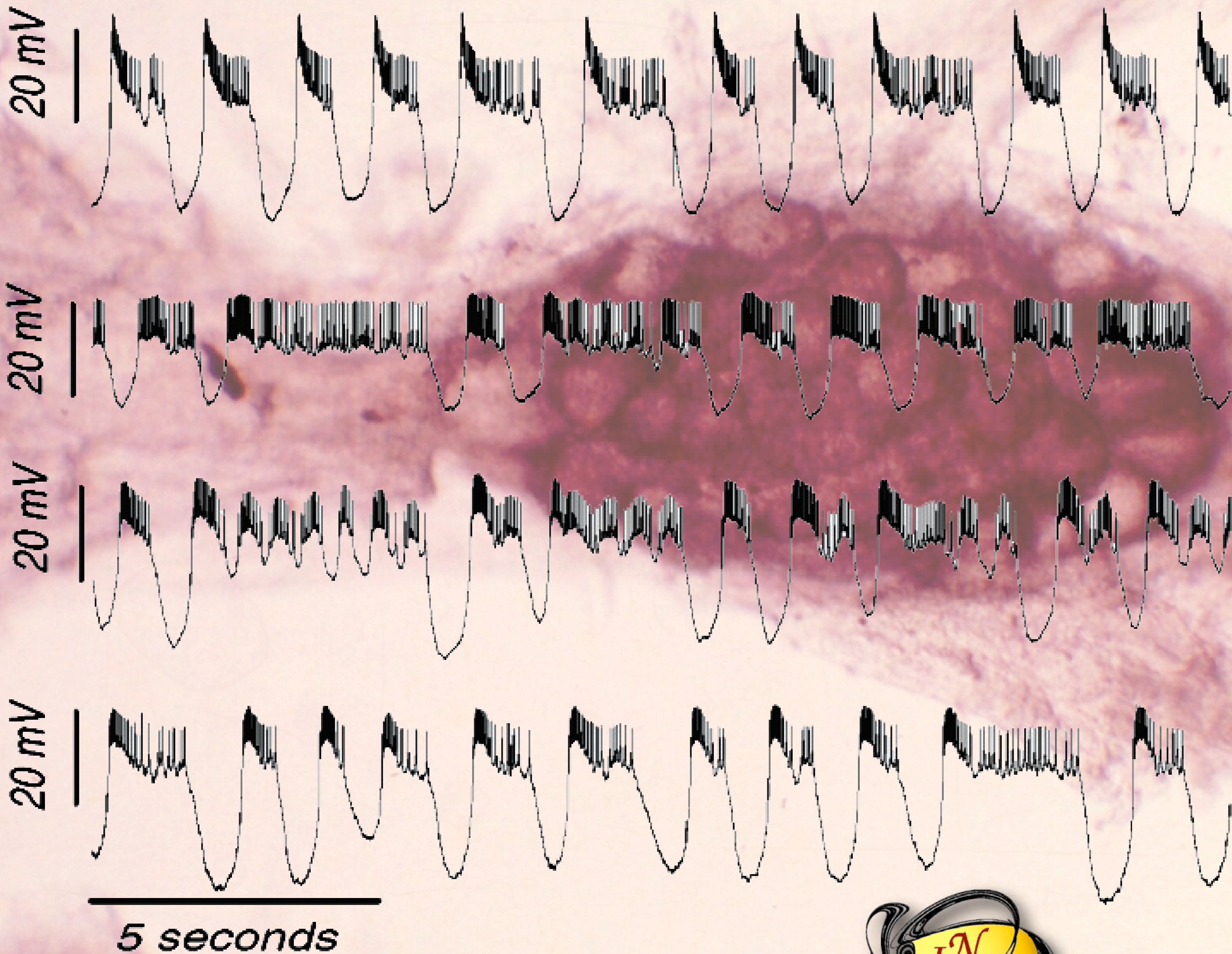
CPG: Central Pattern Generator



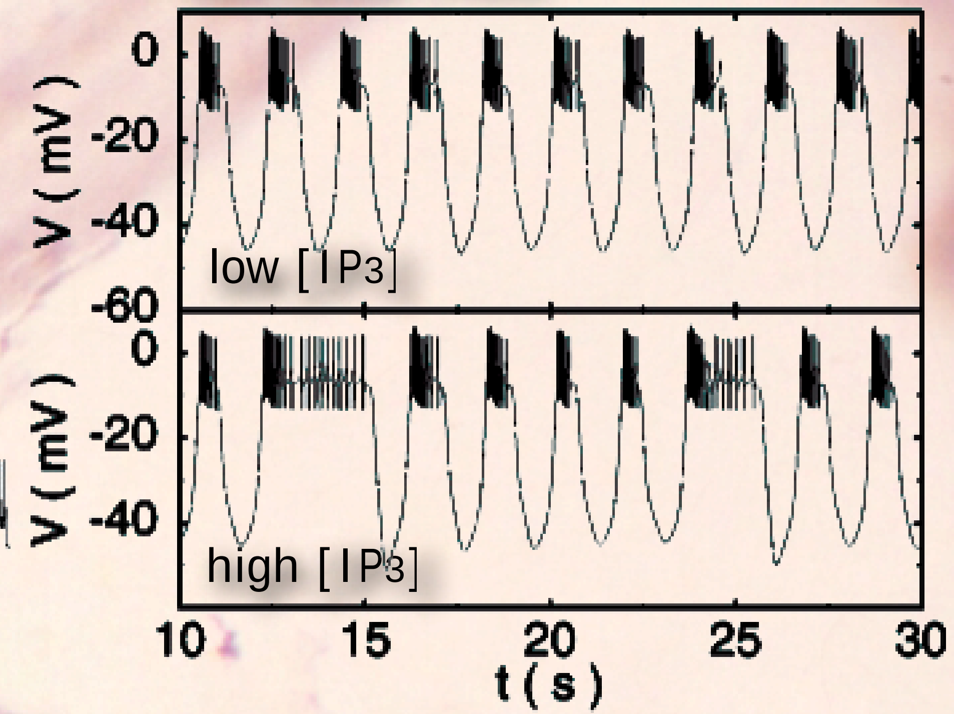

Invertebrate CPGs
Identified Neurons
STIM
AMP
CRO
AMP
STIM
STOMATOGASTRIC GANGLION
E
MUSCLE
Neuronal Circuits
GASTRIC CPG
GM9A
GM1
GPR 2
AGR
APM
MPN
PS
OC
PSR
CG
INT1
AM
DG
LG
MG
GM
LPG
CD1
CD2
AB
VD
IC
PD
LP
PY
P
E
PYLORIC CPG
IVN
Inhibitory
Functional Inhibitory
Modulatory
Excitatory
Functional Excitatory
Electrotonic
Diode
Pattern Generation Mechanisms
LG
MG
LPG
DG
AM
GM
INT1
5s
Synaptic Connectivity
LP
2 mV
4 mV
10 msec
PD
4 mV
5 msec
LP
PD

Dynamical Neuronal Models

When synaptically isolated, lobster LP neurons exhibit only chaotic regimens of bursting

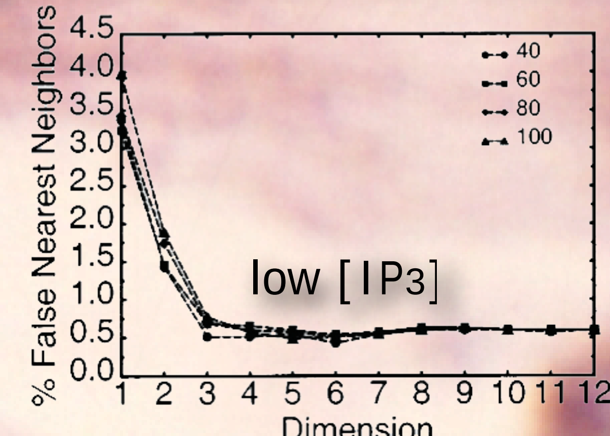


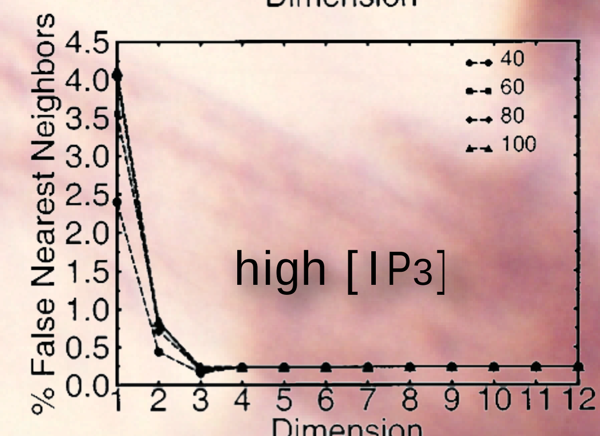
Internal Calcium buffering modulates chaos



Local False Nearest Neighbor Analysis

Lobster neurons have only 4 degrees of dynamical freedom!



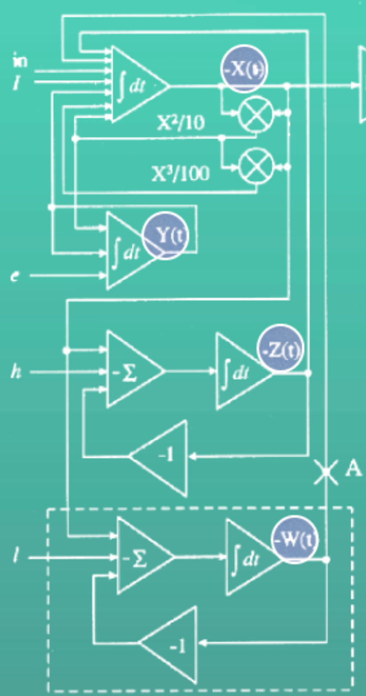


Institute for Nonlinear Science: UCSD

Electronic Neurons and Synapses

Institute for Non-Linear Science
UC San Diego

Hindmarsh Rose Equations



$$\frac{dx(t)}{dt} = ay(t) + bx^2(t) - cx^3(t) - dz(t) + i + i_{syn}$$

Membrane Potential

$$\frac{dy(t)}{dt} = e - fx^2(t) - y(t) - gw(t)$$

Fast Conductances

$$\frac{dz(t)}{dt} = m(-z(t) + S(x(t) + h))$$

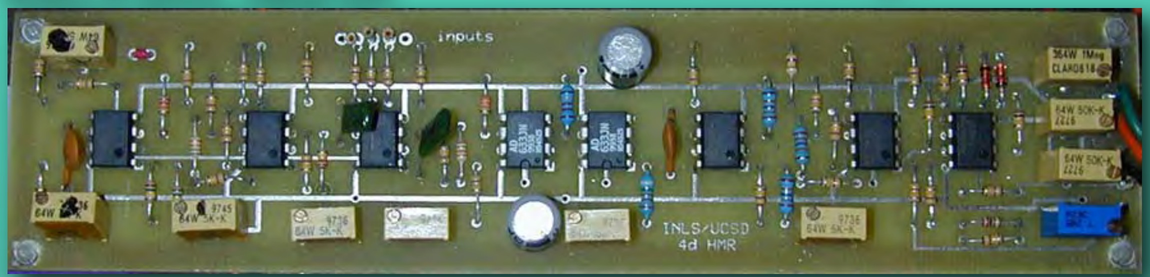
Slow Conductances

$$\frac{dw(t)}{dt} = n(-kw(t) + r(y(t) + l))$$

Calcium Dynamics

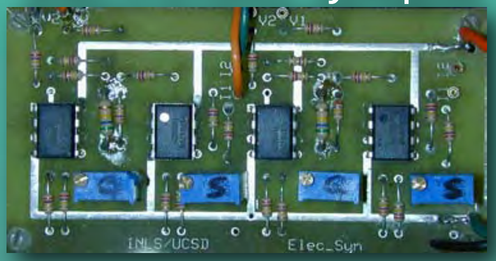
Institute for Nonlinear Science: UCSD

electronic neuron

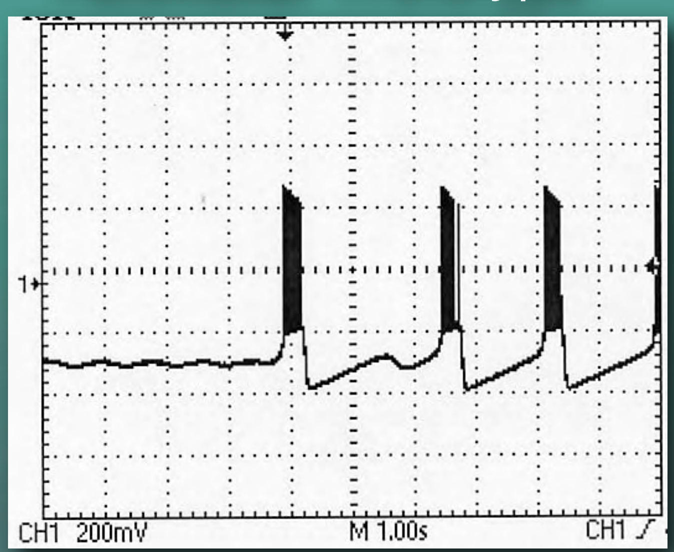


chemical synapse

electrotonic synapse

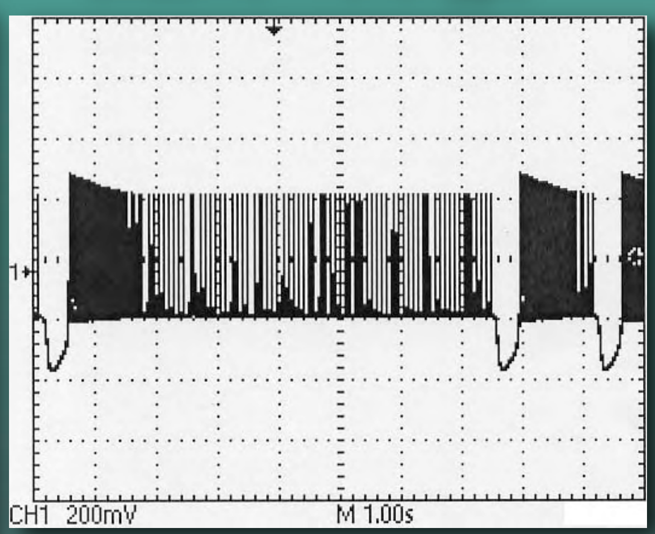


Pacemaker Prototype

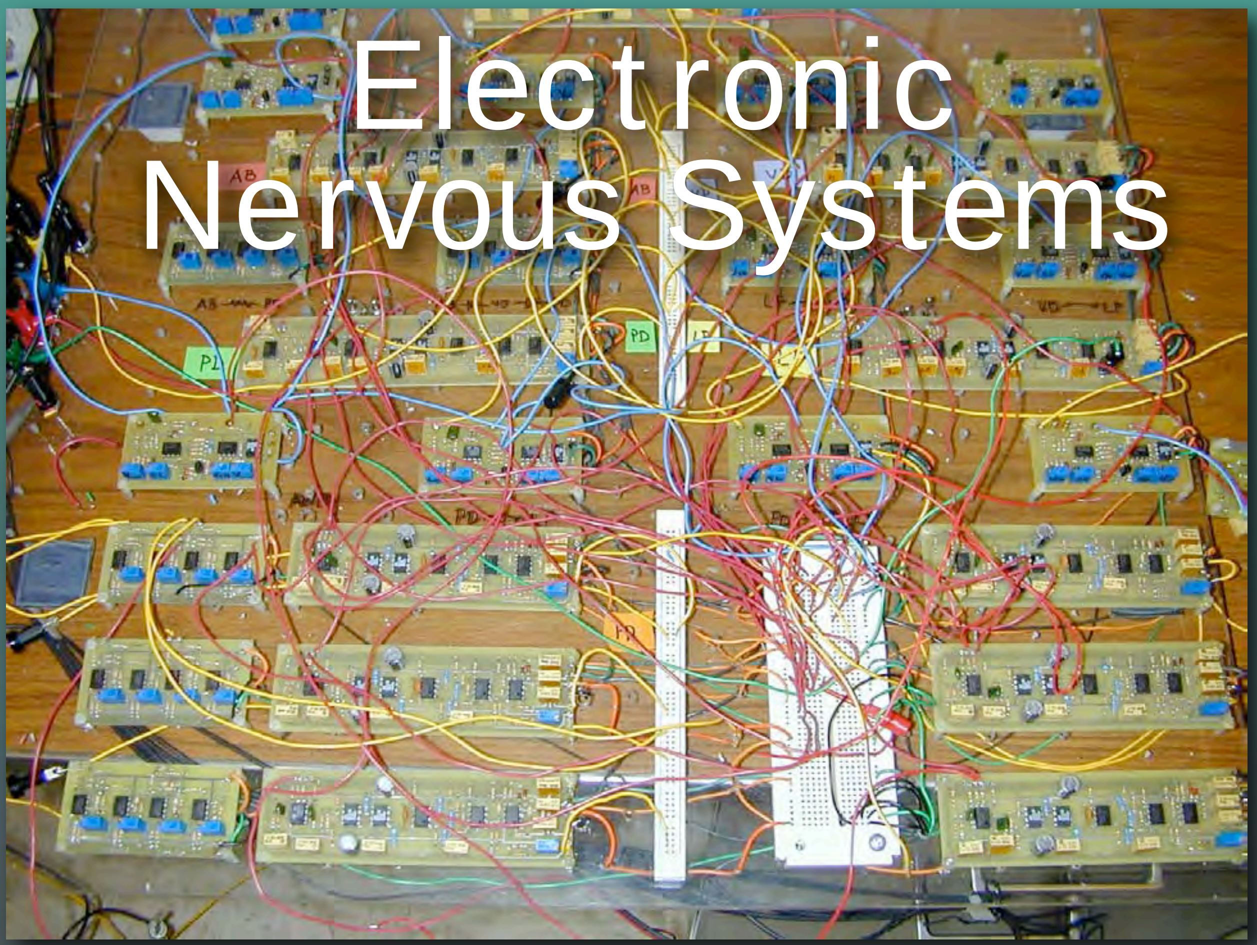


g	0
n	1750
m	230
I (V)	2.21
i (V)	5.78
e (V)	0
h (V)	-3.48

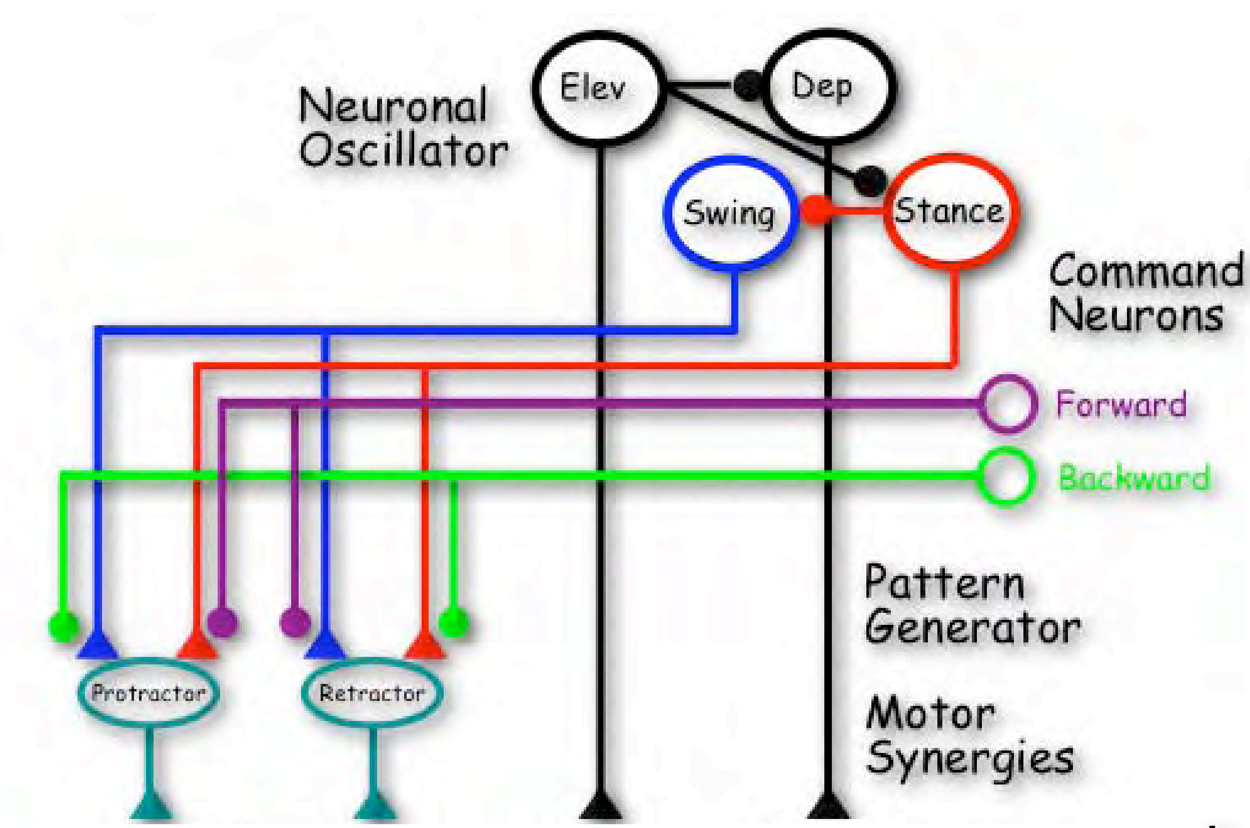
Chaotic Prototype

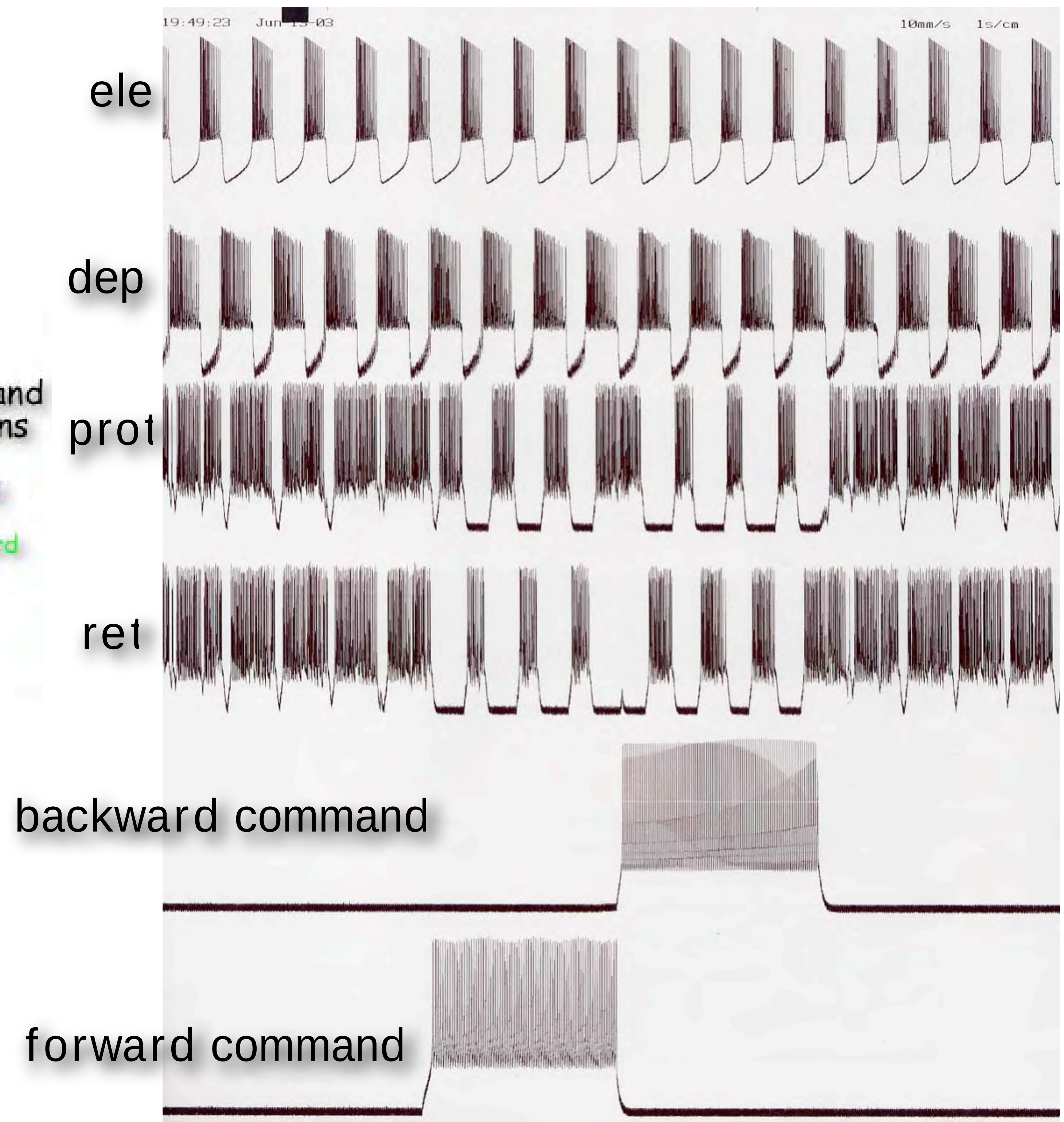


g (ohms)	0
n(ohms)	1750
m(ohms)	230
I (V)	2.21
i (V)	5.78
e (V)	1.18
h (V)	-3.48

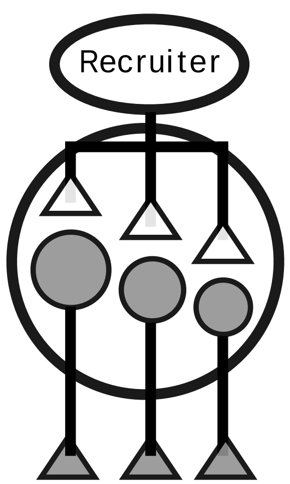


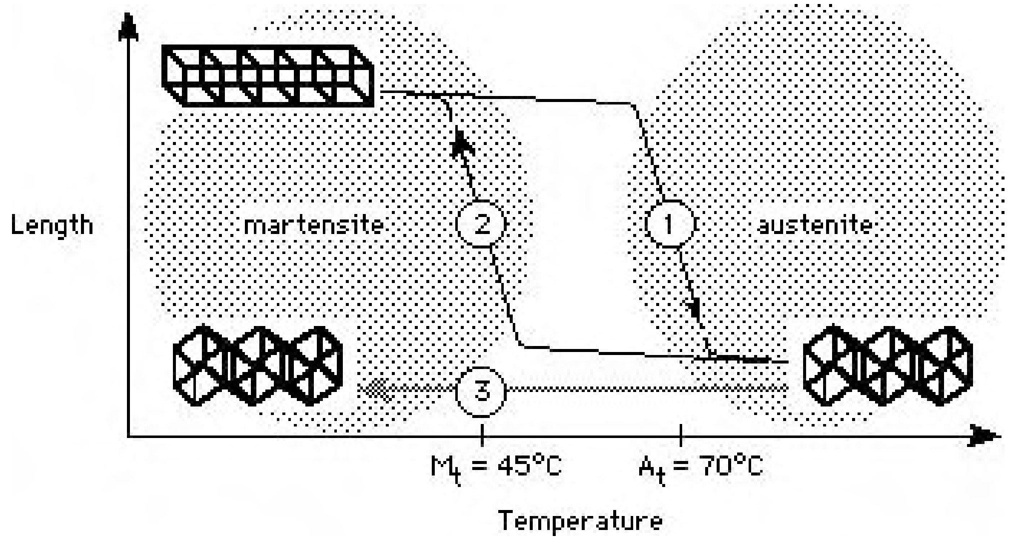
Controlling Walking With EN Networks





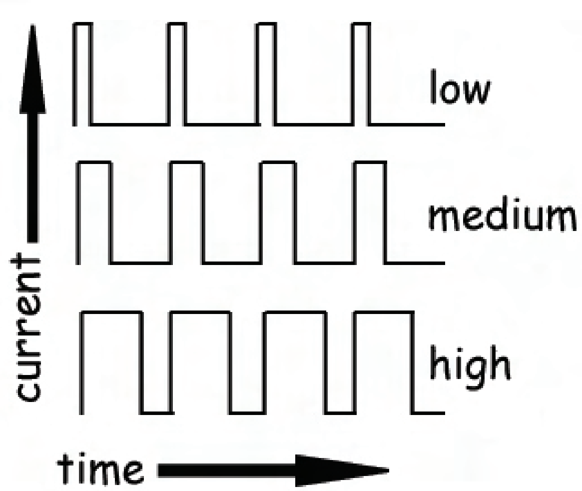
Myomorphic Actuators





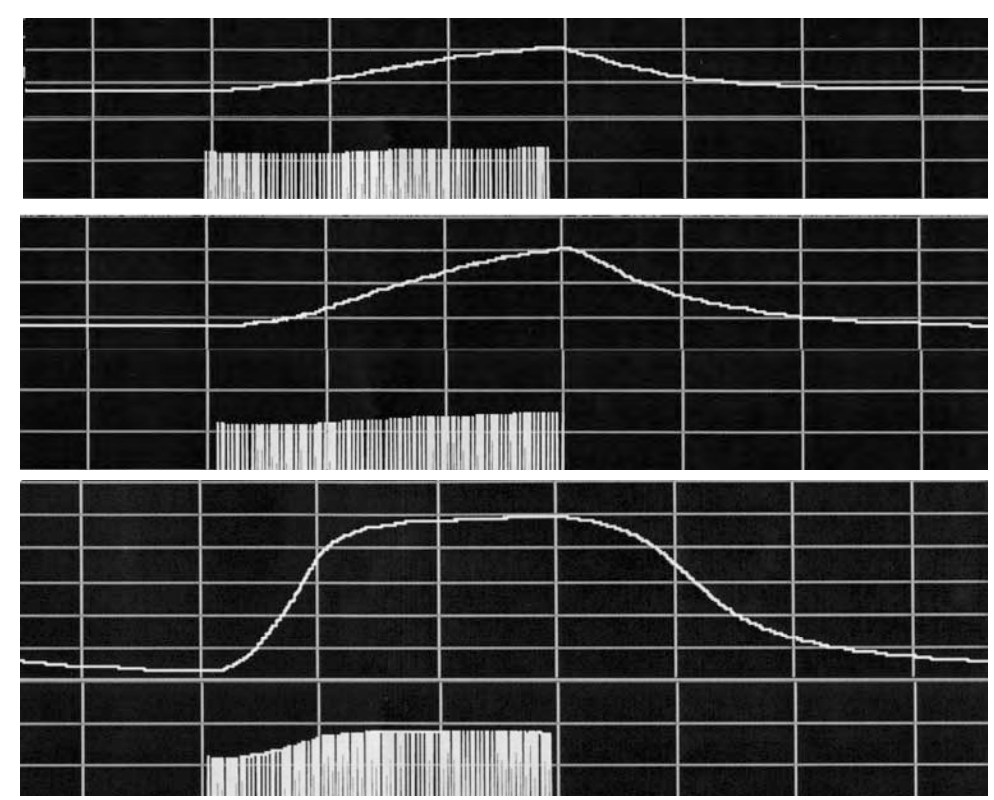
Size Principle:
Motor units are recruited in the order of increasing size which determines their force generation capability

Pulse Width Duty Cycle Modulation
Size principle realized by discrete increasing duty cycles



- Artificial Muscle
  Nitinol: 50/50 Alloy of Nickel and Titanium.
- Two stable crystalline states
- State transformation to elongated state can be induced by mechanical deformation
- Transformation temperature reached through heating the wire by passing an electrical current through it causing conversion to austenite and shortening

Graded Contractions



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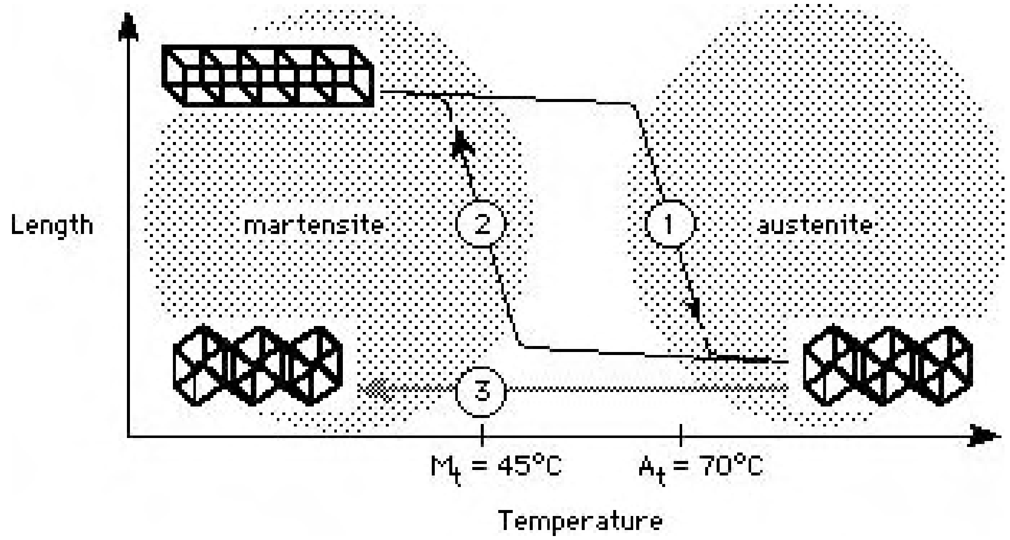
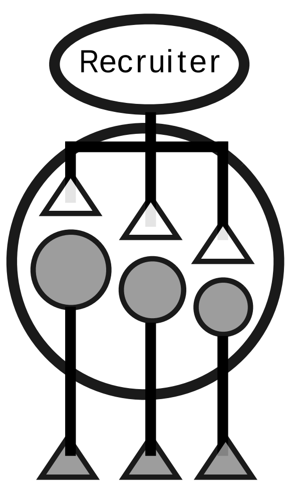
Myomorphic Actuators

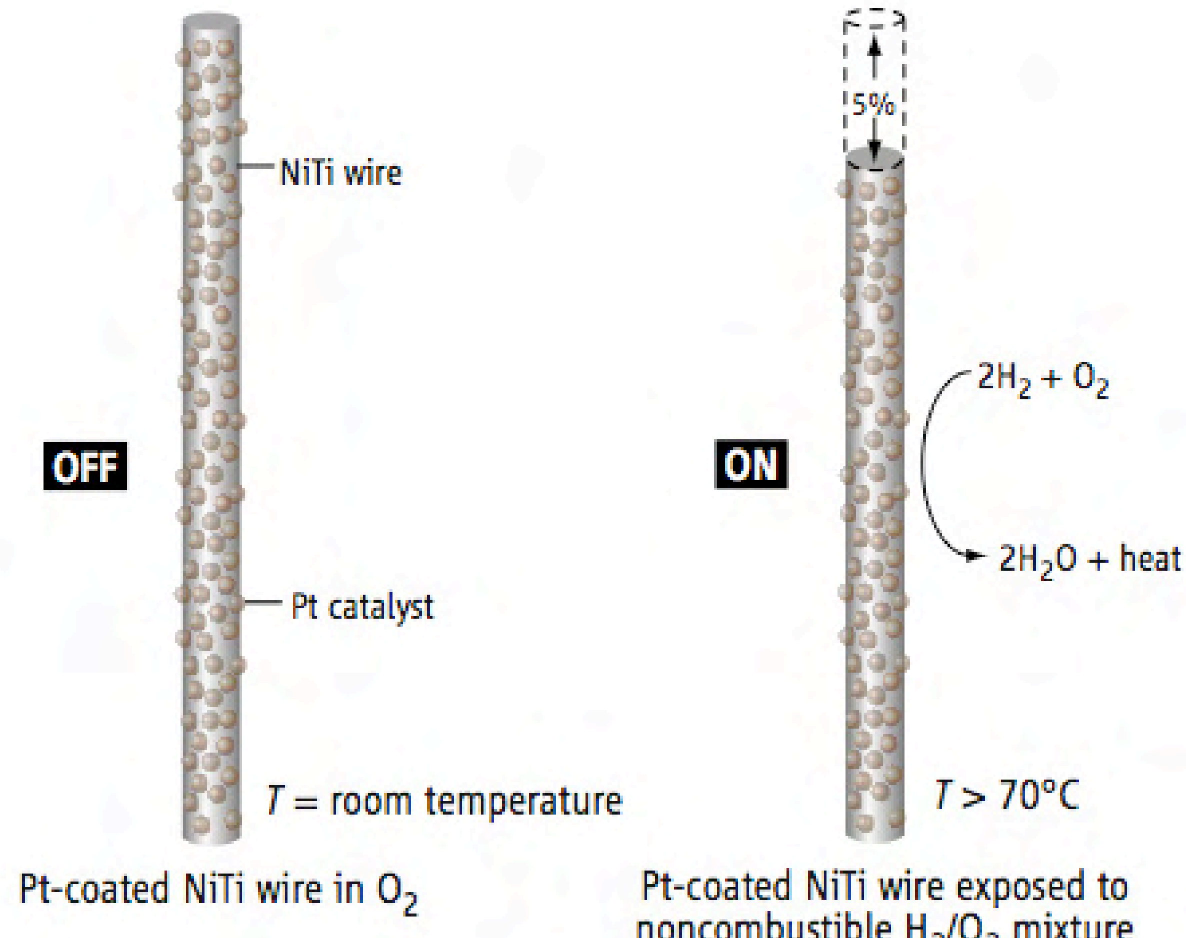


- **Artificial Muscle**
  Nitinol: 50/50 Alloy of Nickel and Titanium.
- Two stable crystalline states
- State transformation to elongated state can be induced by mechanical deformation
- Transformation temperature reached through heating the wire



Fuel Cell actuated Nitinol

Tensile actuator. (Left) Nickel titanium shape memory alloys can also be used as actuators. The NiTi wire is coated with platinum catalyst. **(Right)** When dissolved hydrogen and oxygen react on the platinum coating to produce water, the resulting heat induces a phase change in the NiTi leading to contraction and force generation (*2*). Both actuator reactions are reversible.



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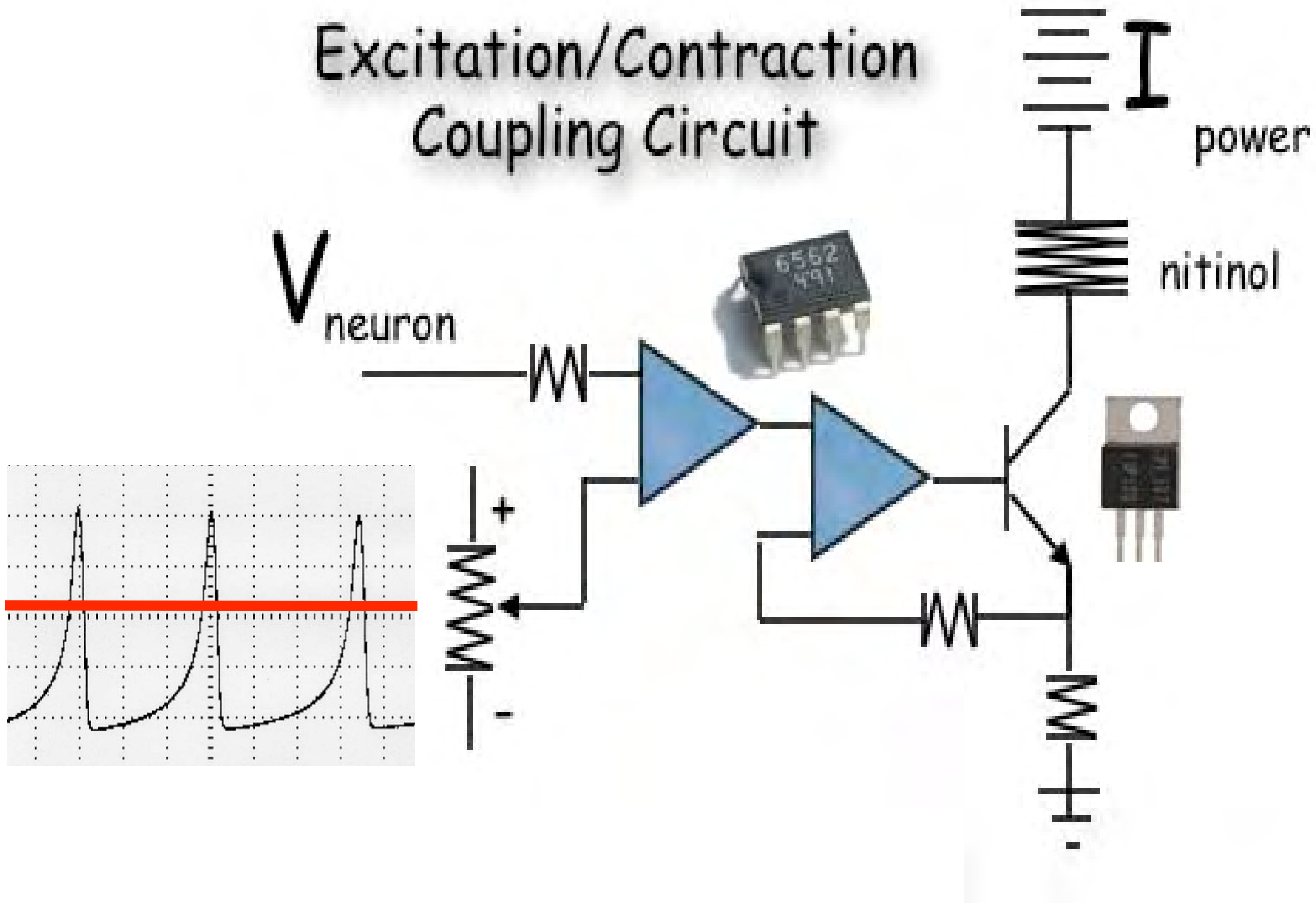
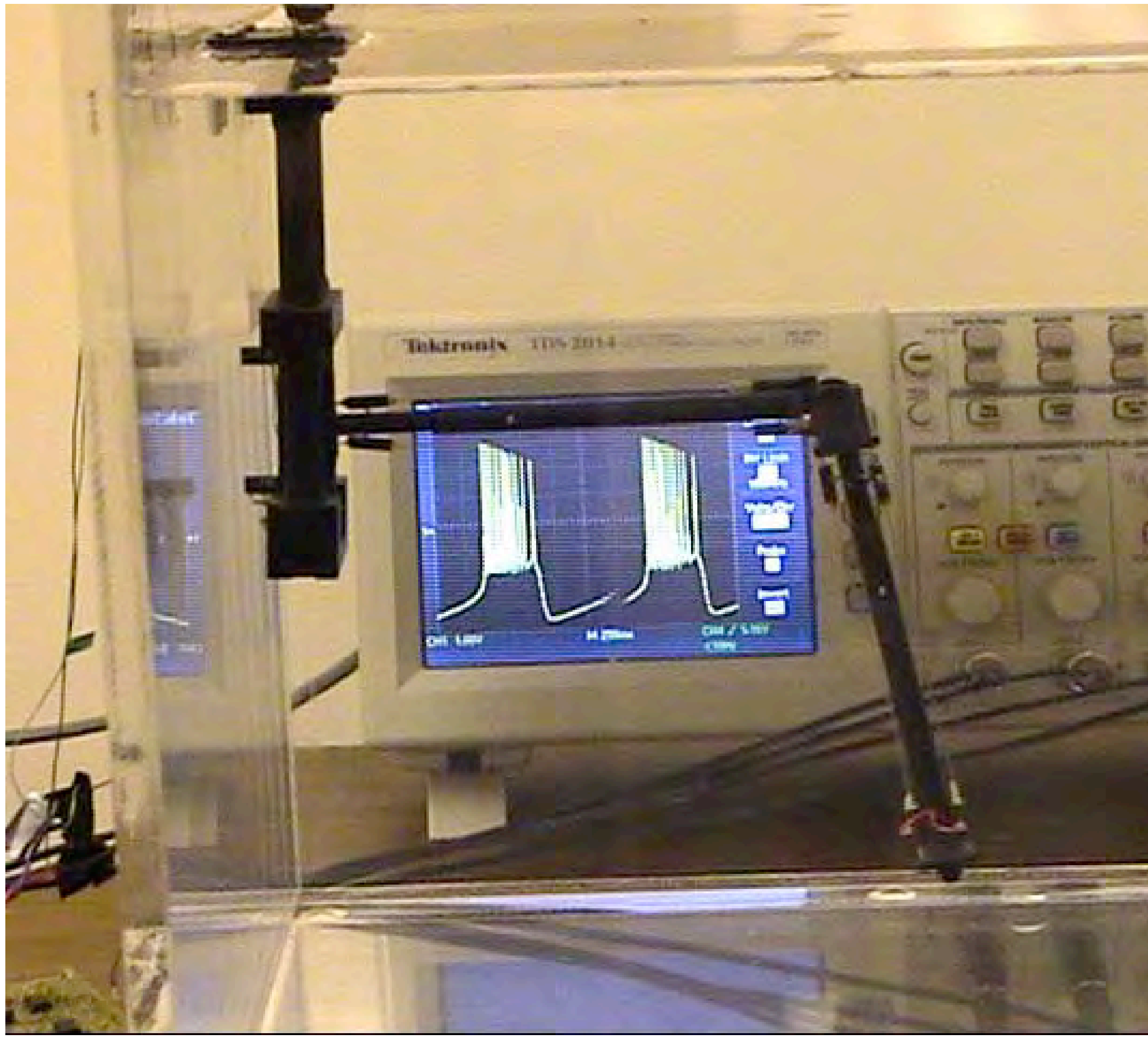
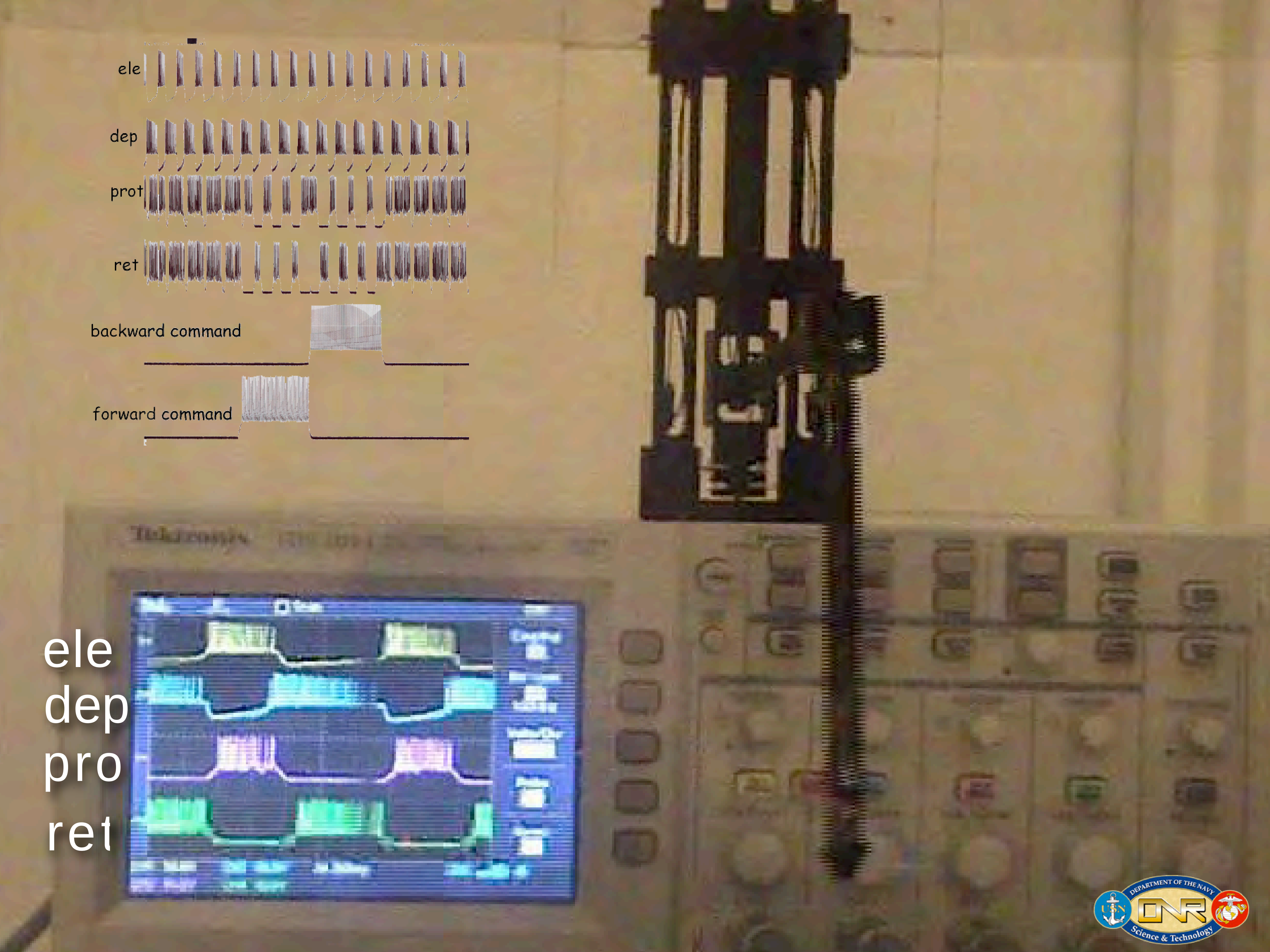
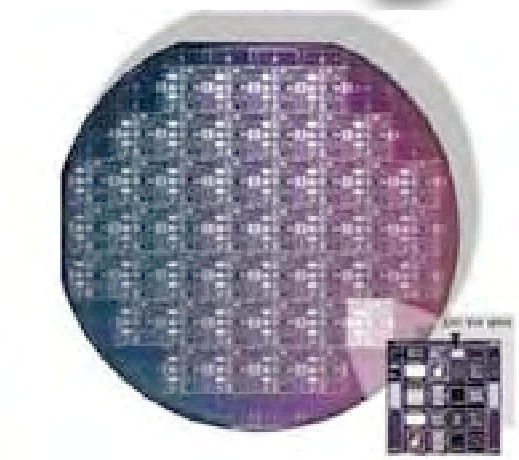
Activating Nitinol With Electronic Neurons






ele
dep
prot
ret
backward command
forward command
ele
dep
pro
ret

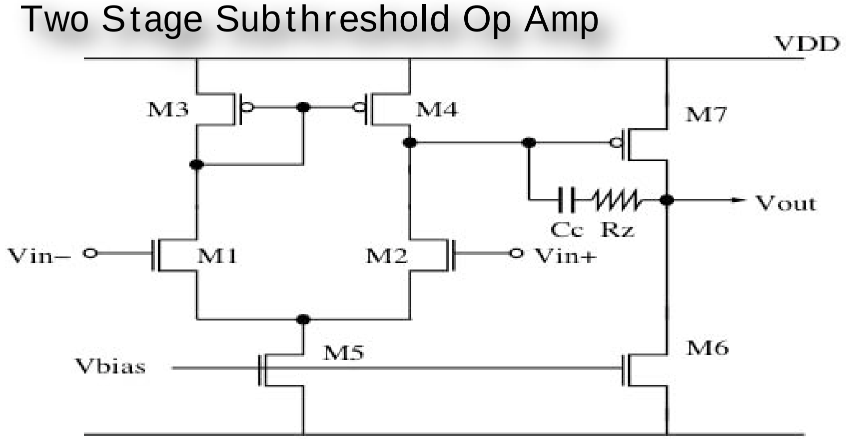
analog VLSI



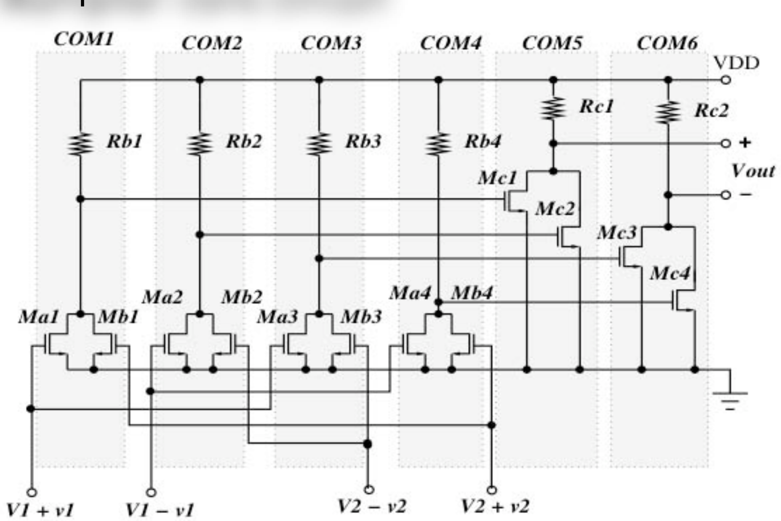
Prof Yong-Bin Kim
Dept of ECE
Northeastern Univ.

Fabrication Process : TSMC 0.25um
Supply voltage : 2Volt
Power consumption : 160uW for 3d neuron
100uW for motor neuron

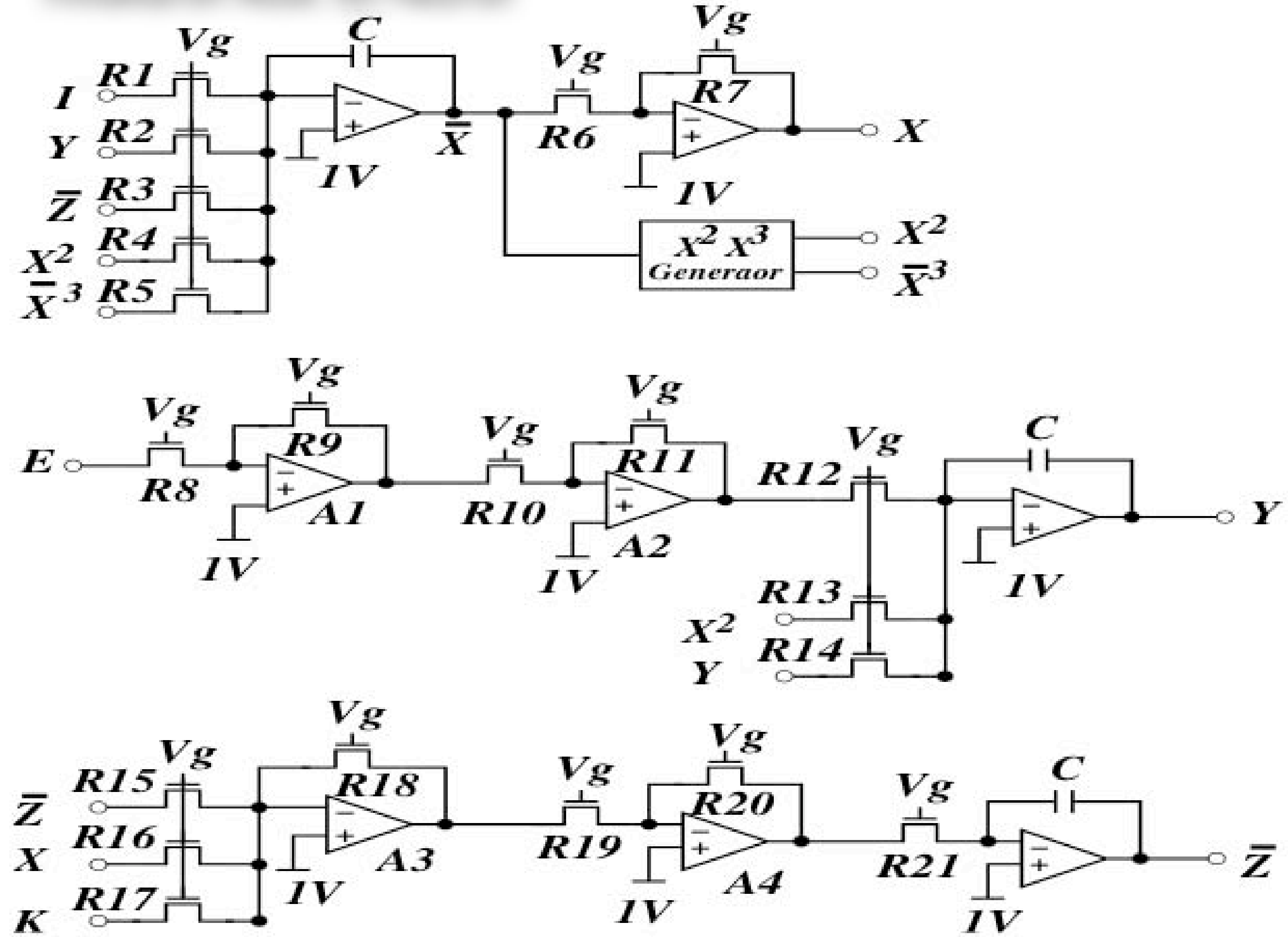
Two Stage Subthreshold Op Amp



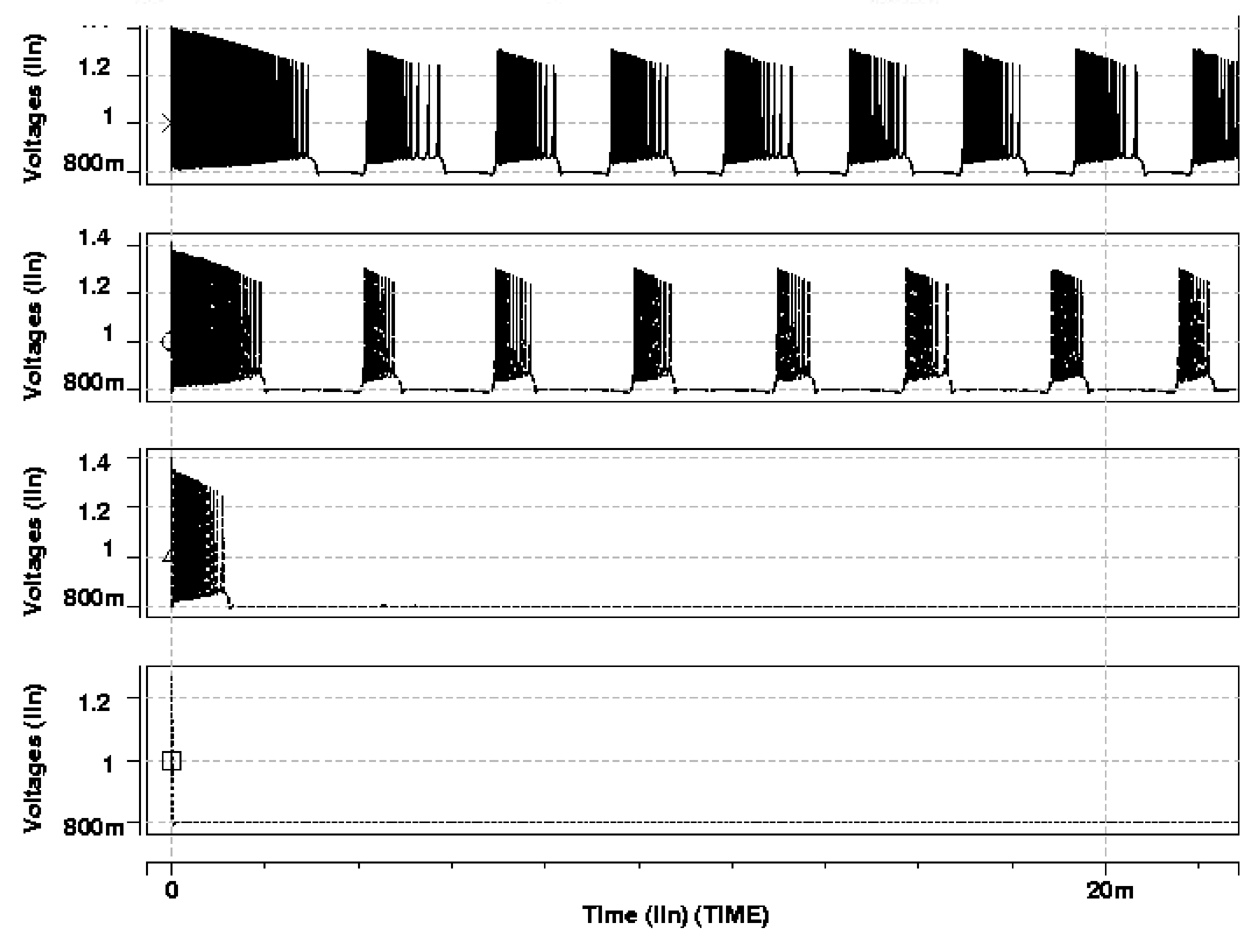
Multiplier Core Circuit



Hindmarsh-Rose 3D Neuron

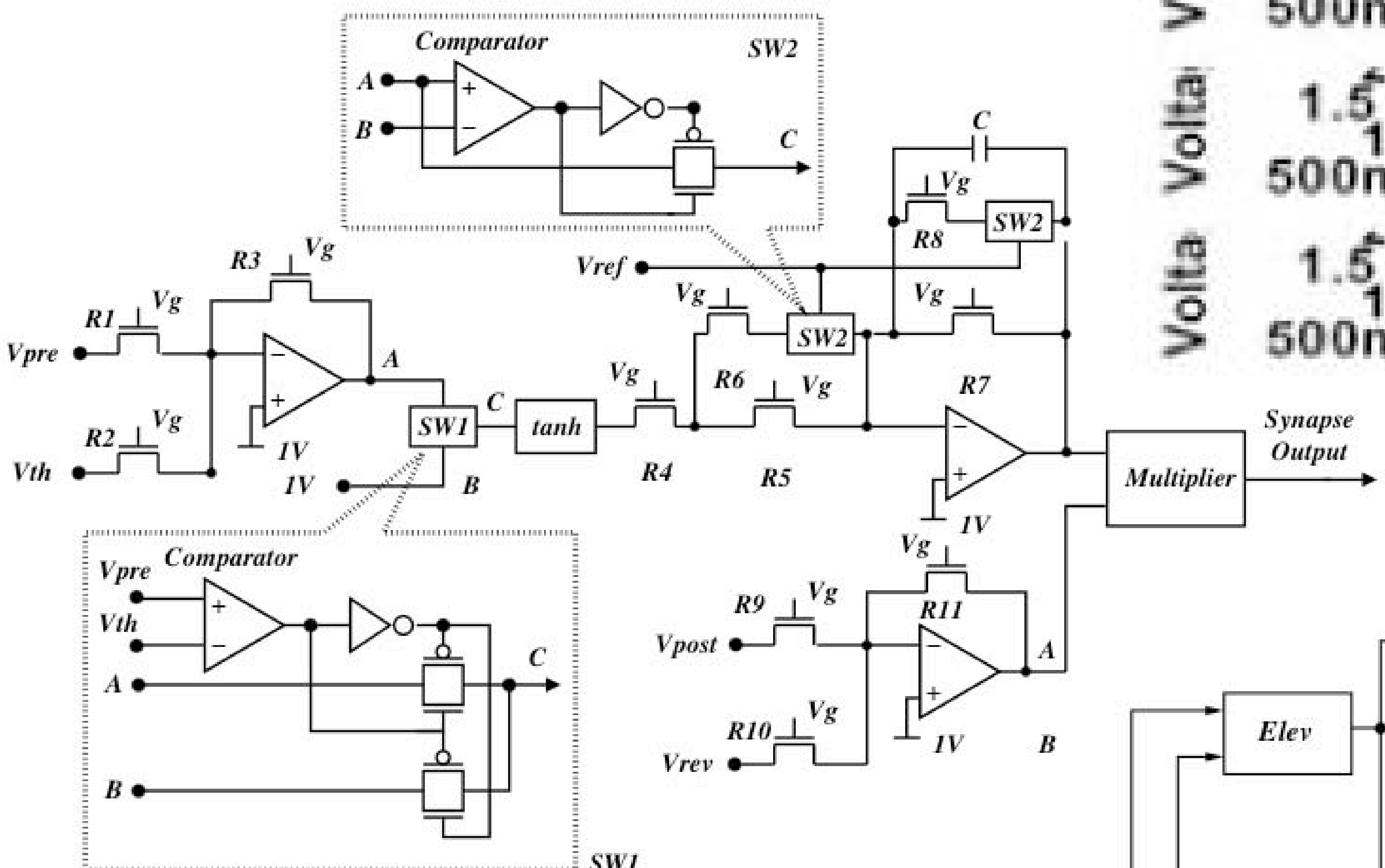


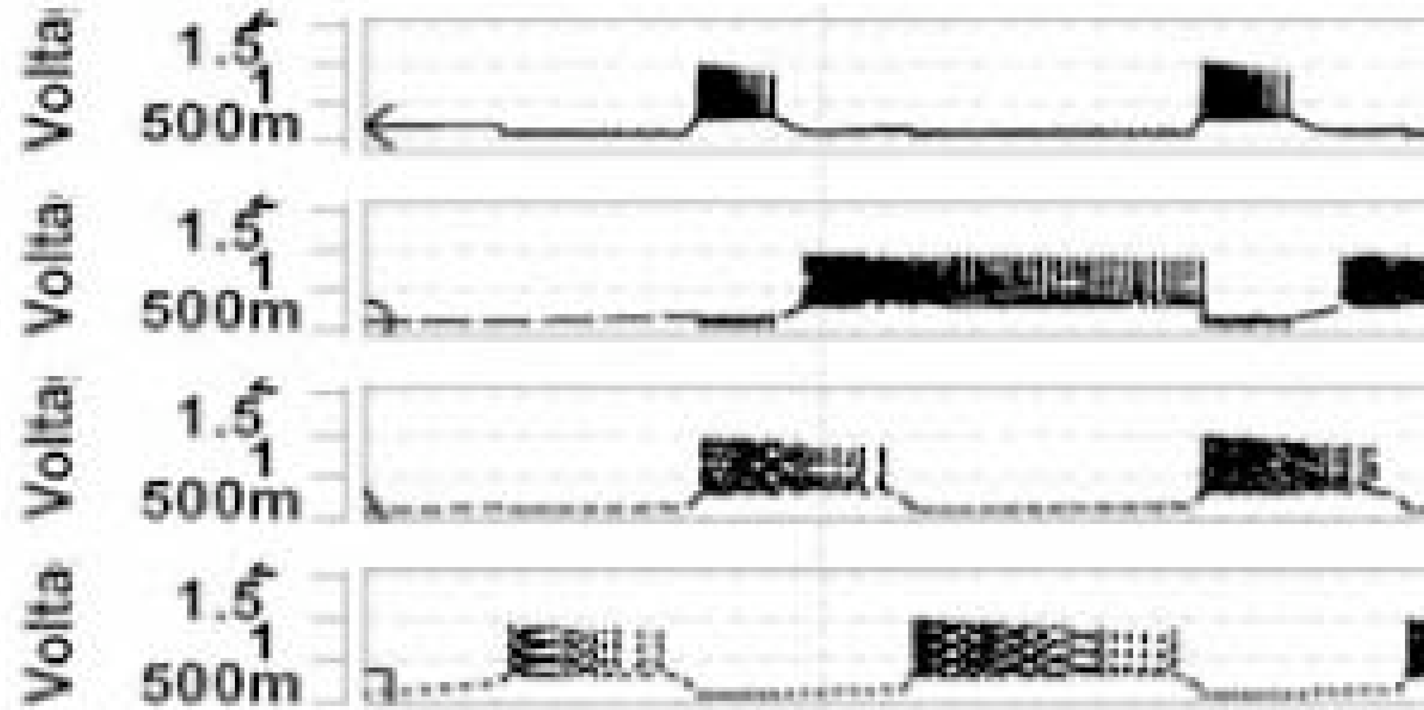
3D



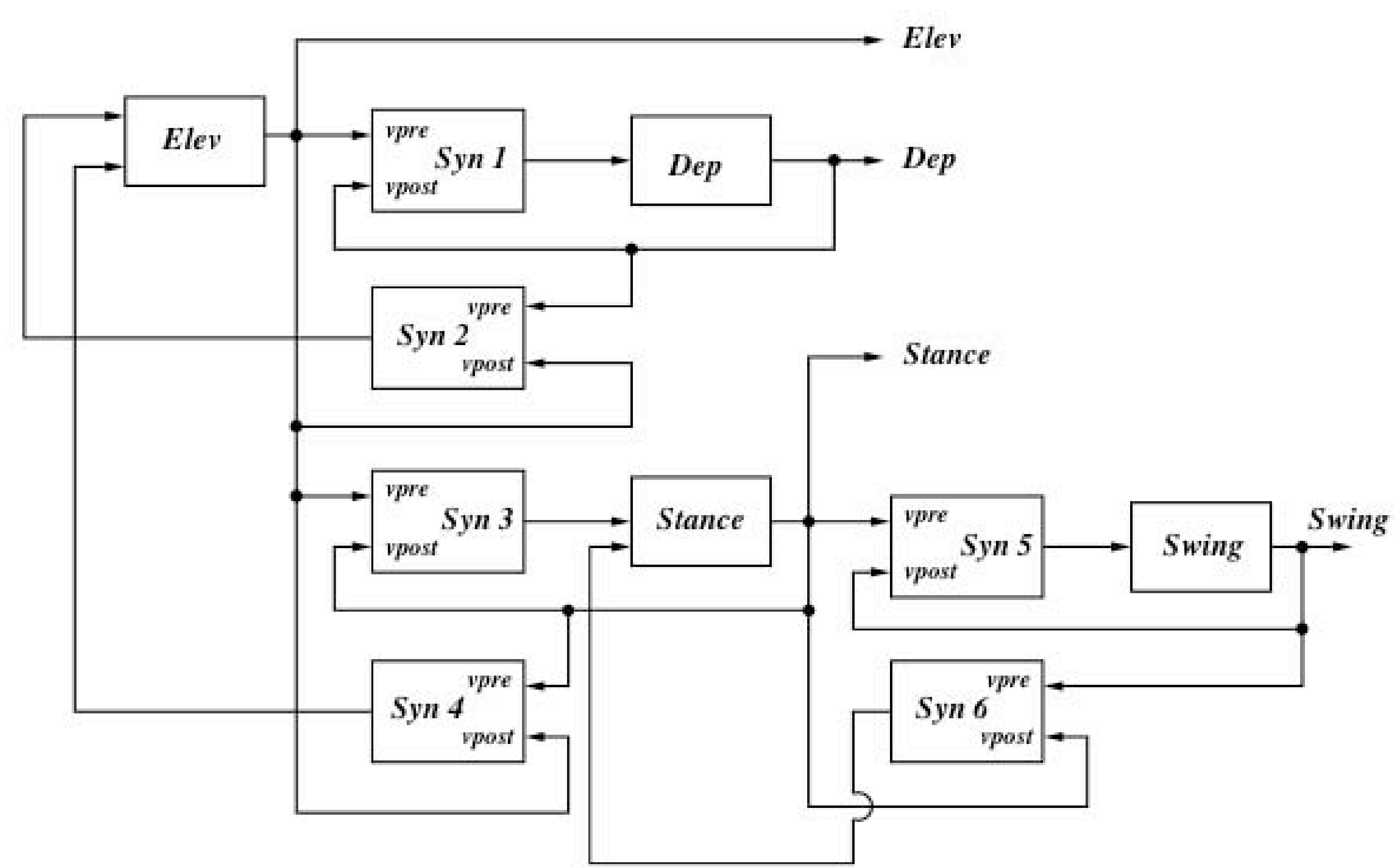
analog VLSI

Chemical Synapse





Core CPG



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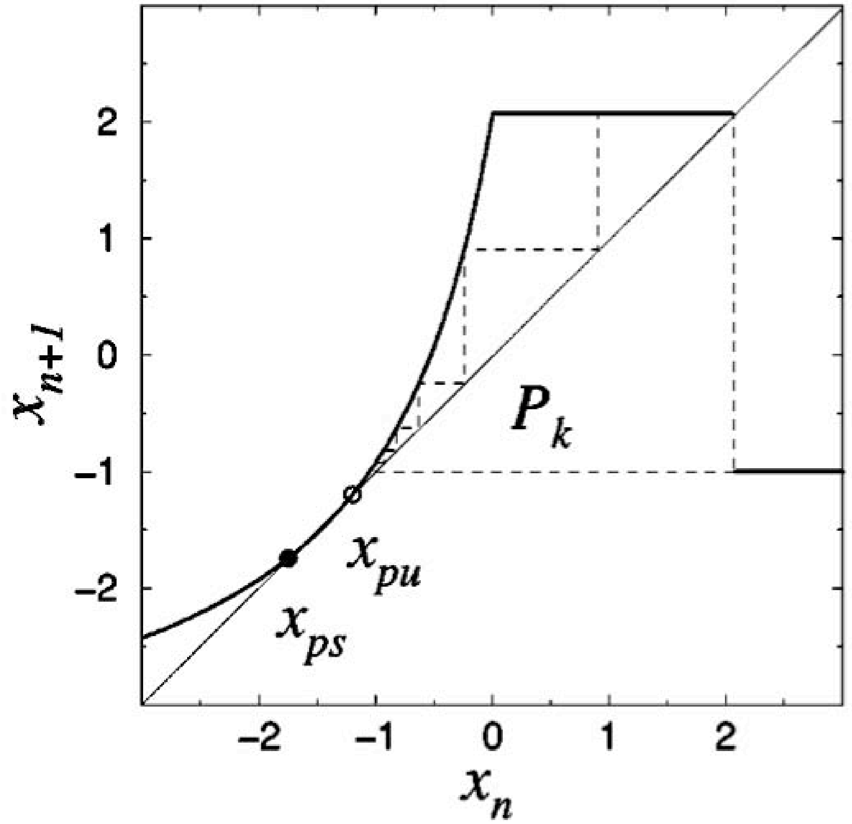
Dept of ECE
Northeastern Univ.

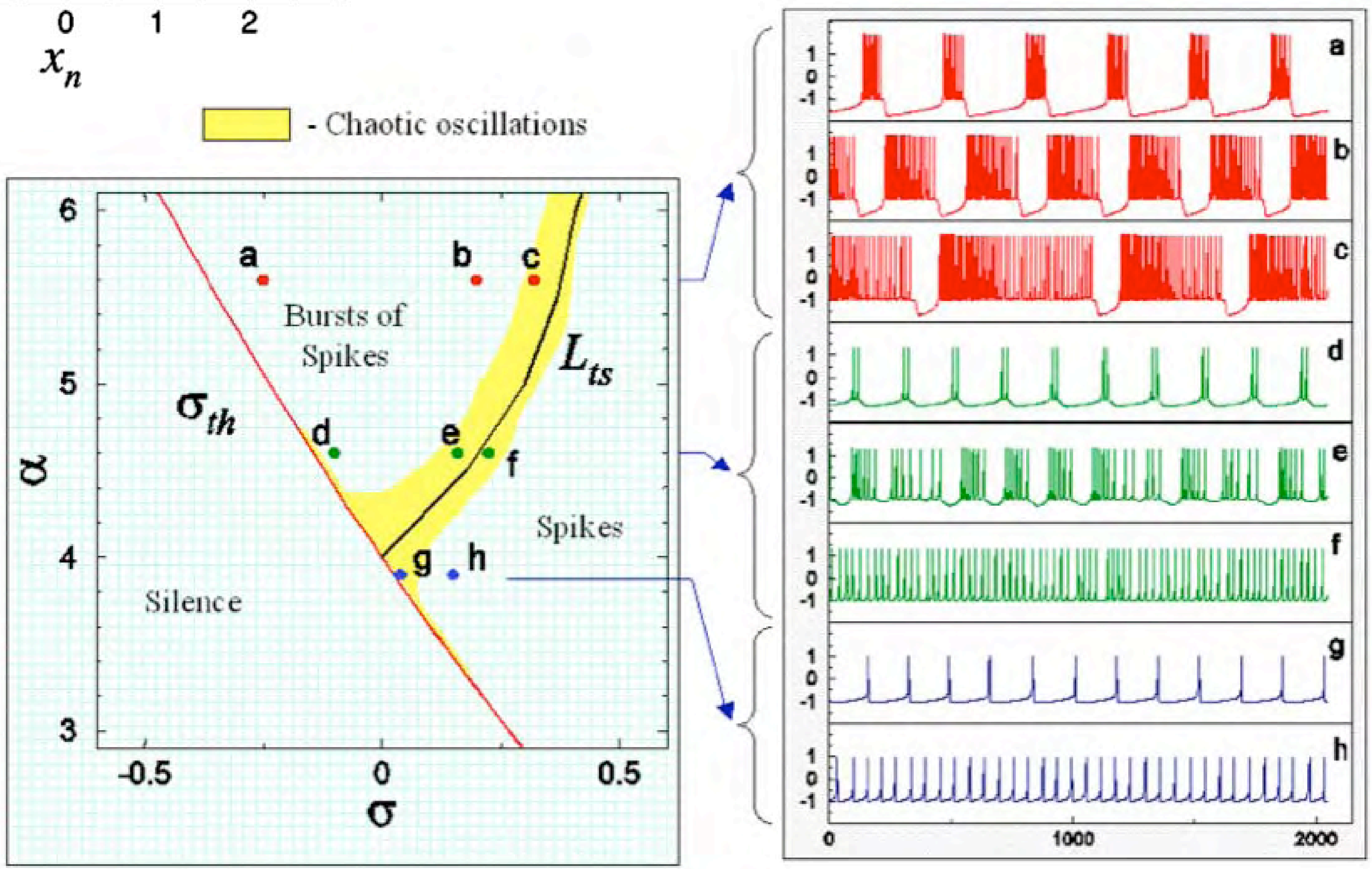
Discrete-Time Map-based Neurons



$$x(n+1)=f(x(n),y(n))$$

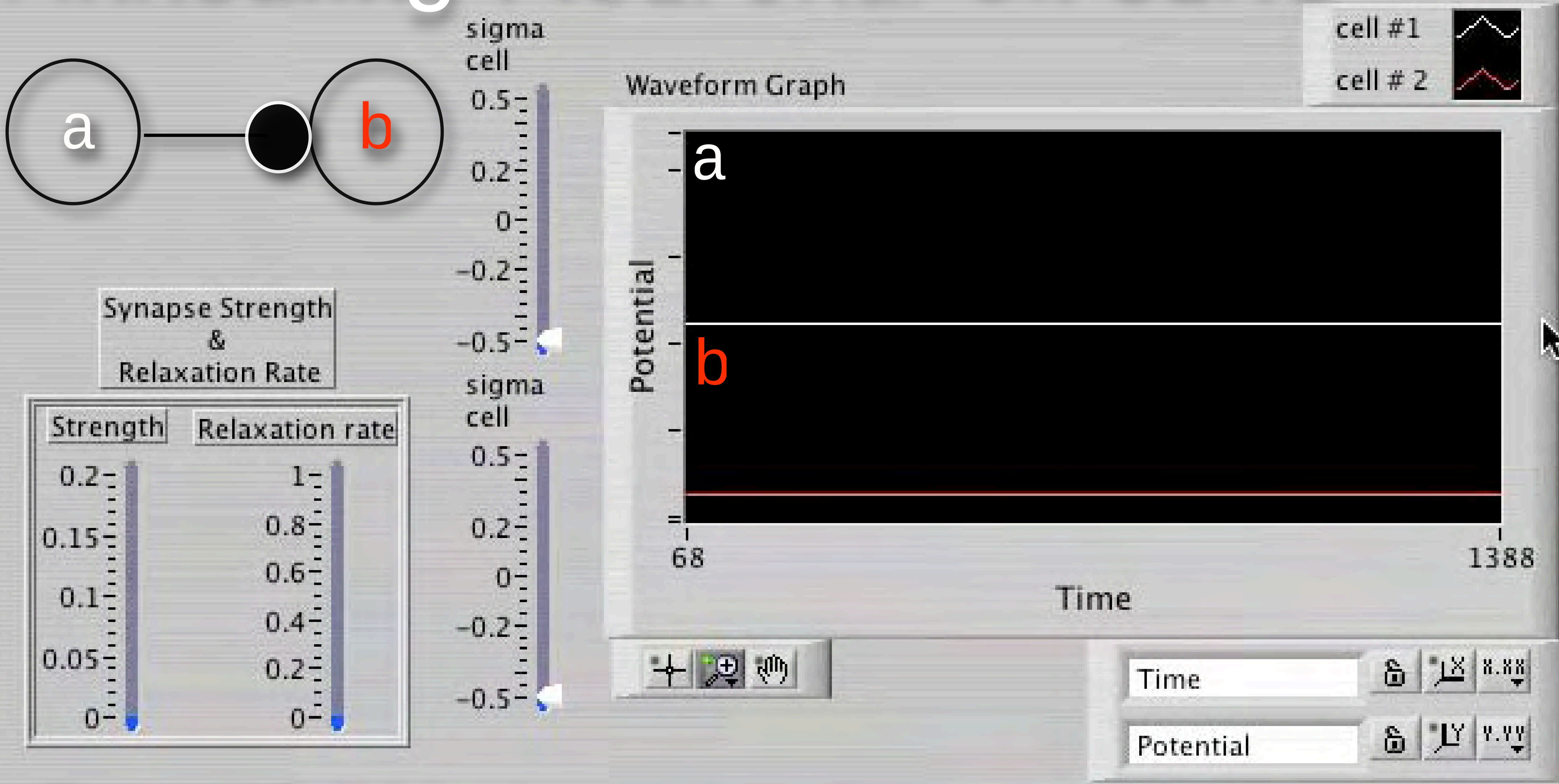
$$f(x,y)=\begin{cases}\alpha/(1-x)+y, & x\leqslant 0\\ \alpha+y, & 0<x<\alpha+y\\ -1, & x\geqslant \alpha+y,\end{cases}$$

$$y_{n+1}=y_n-\mu(x_n+1)+\mu\sigma_n$$



Nikolai
Rulkov

Annealing Neuronal Circuits



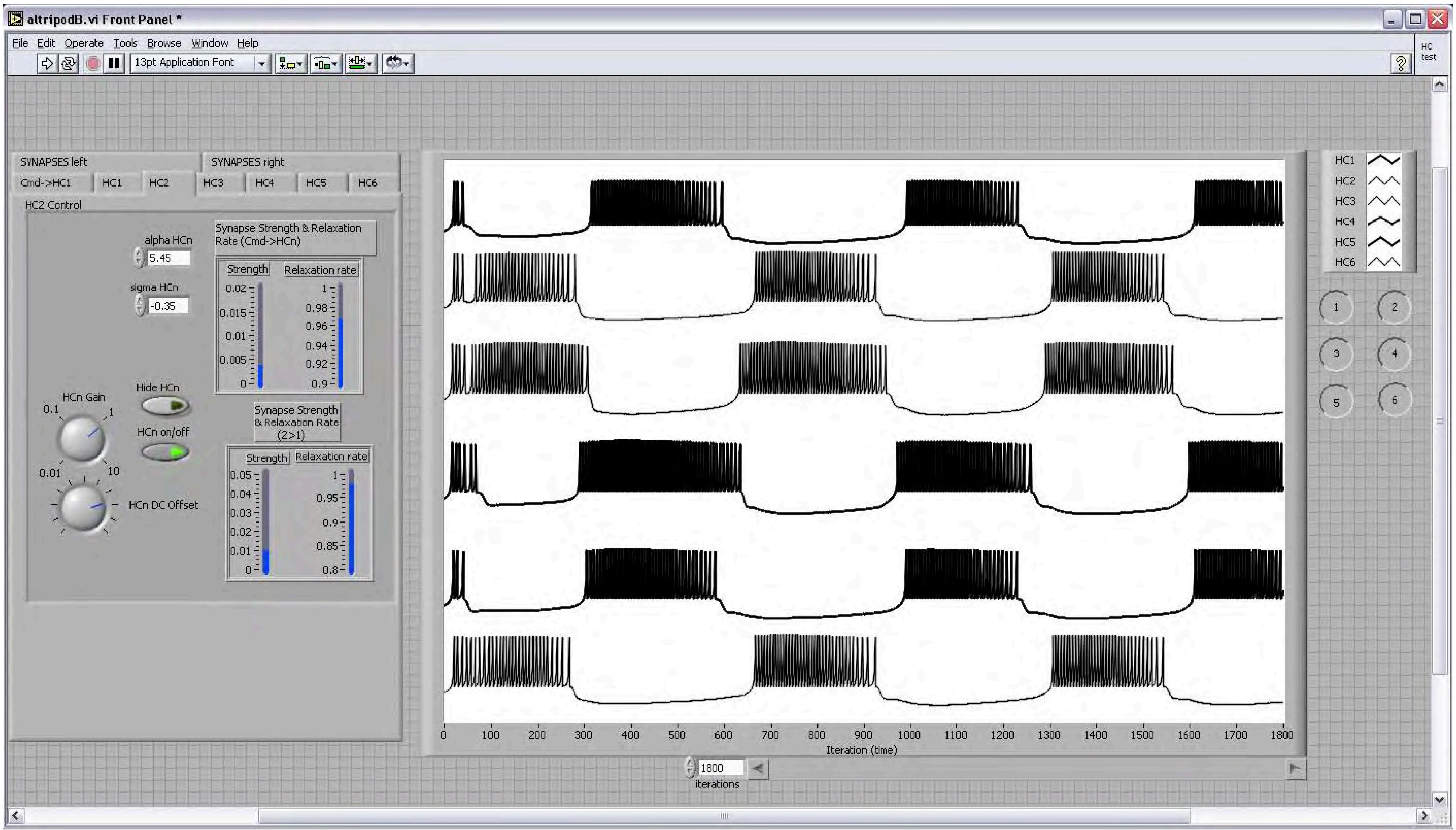
Turn on Cell 1 by increasing sigma

Turn on Cell 2 by increasing sigma

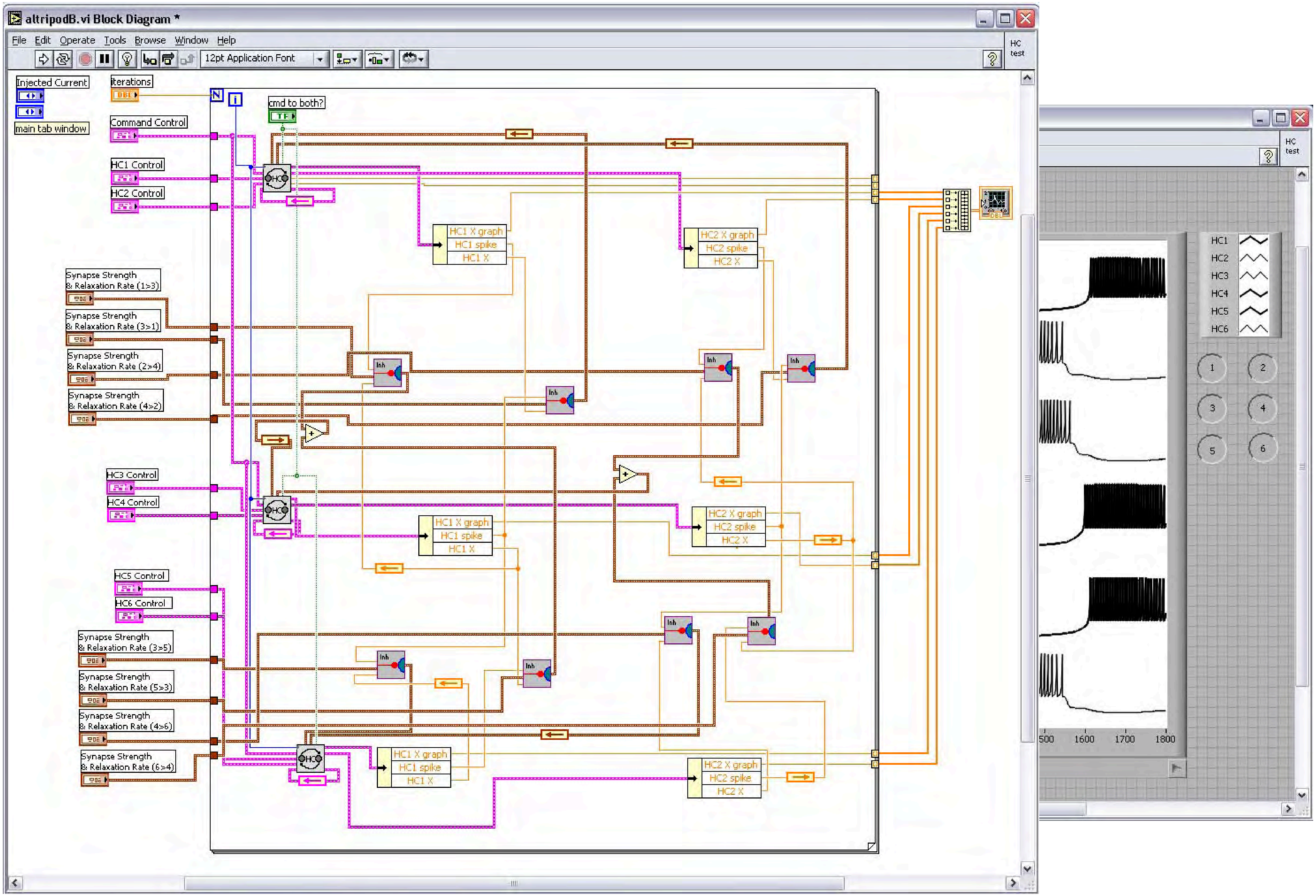
Increase synaptic strength

Adjust synaptic time constant

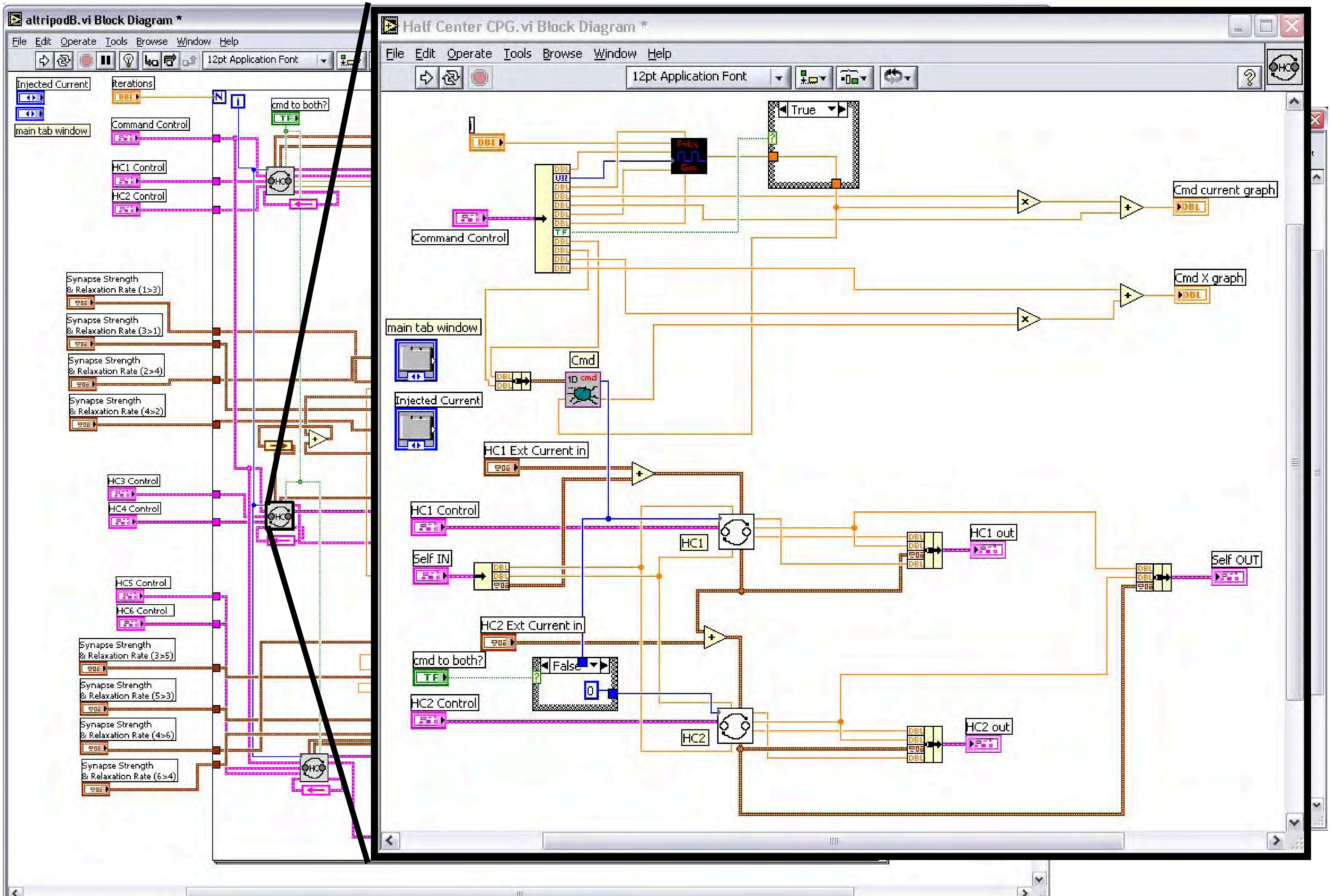
Working with map-based neurons



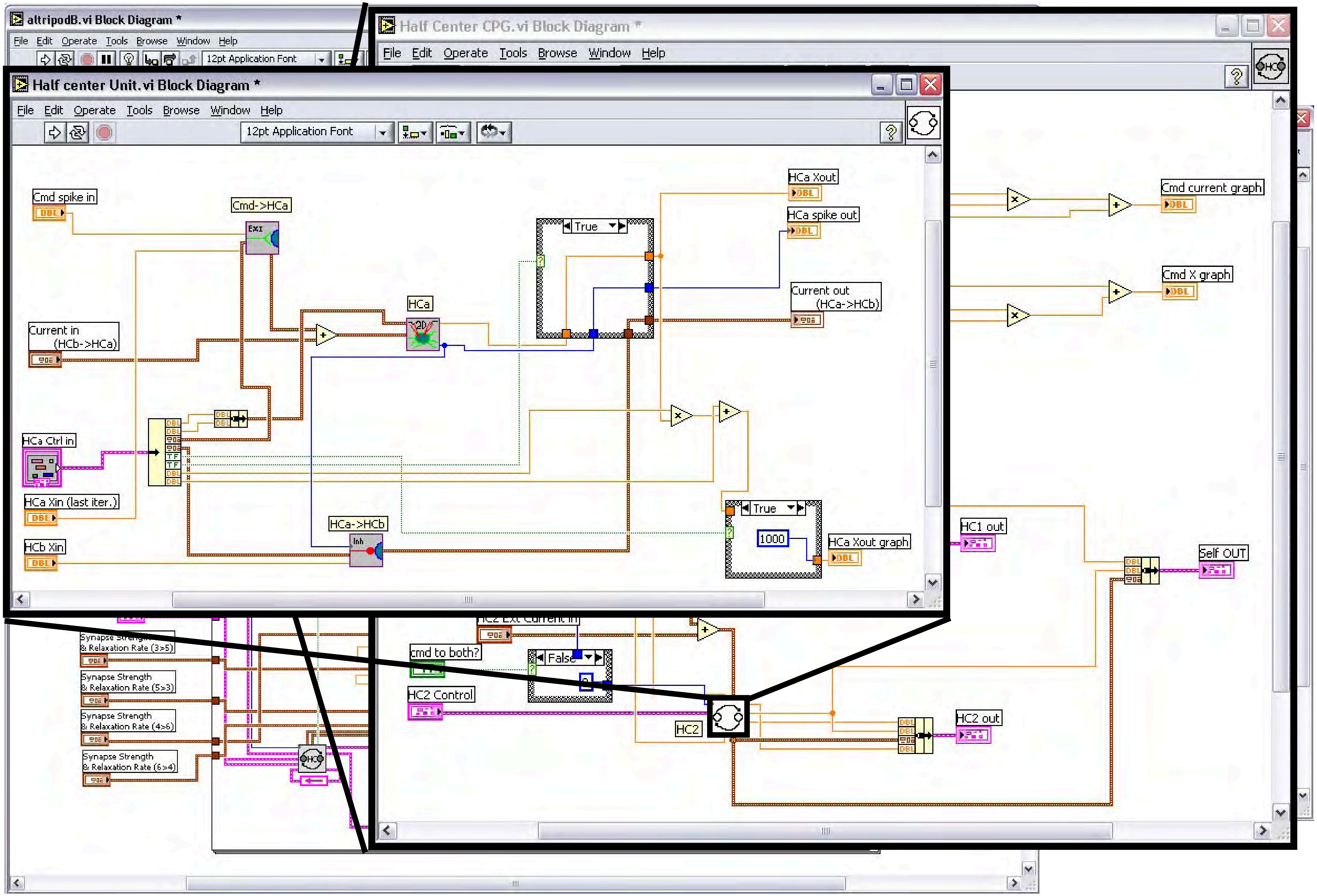
Working with map-based neurons



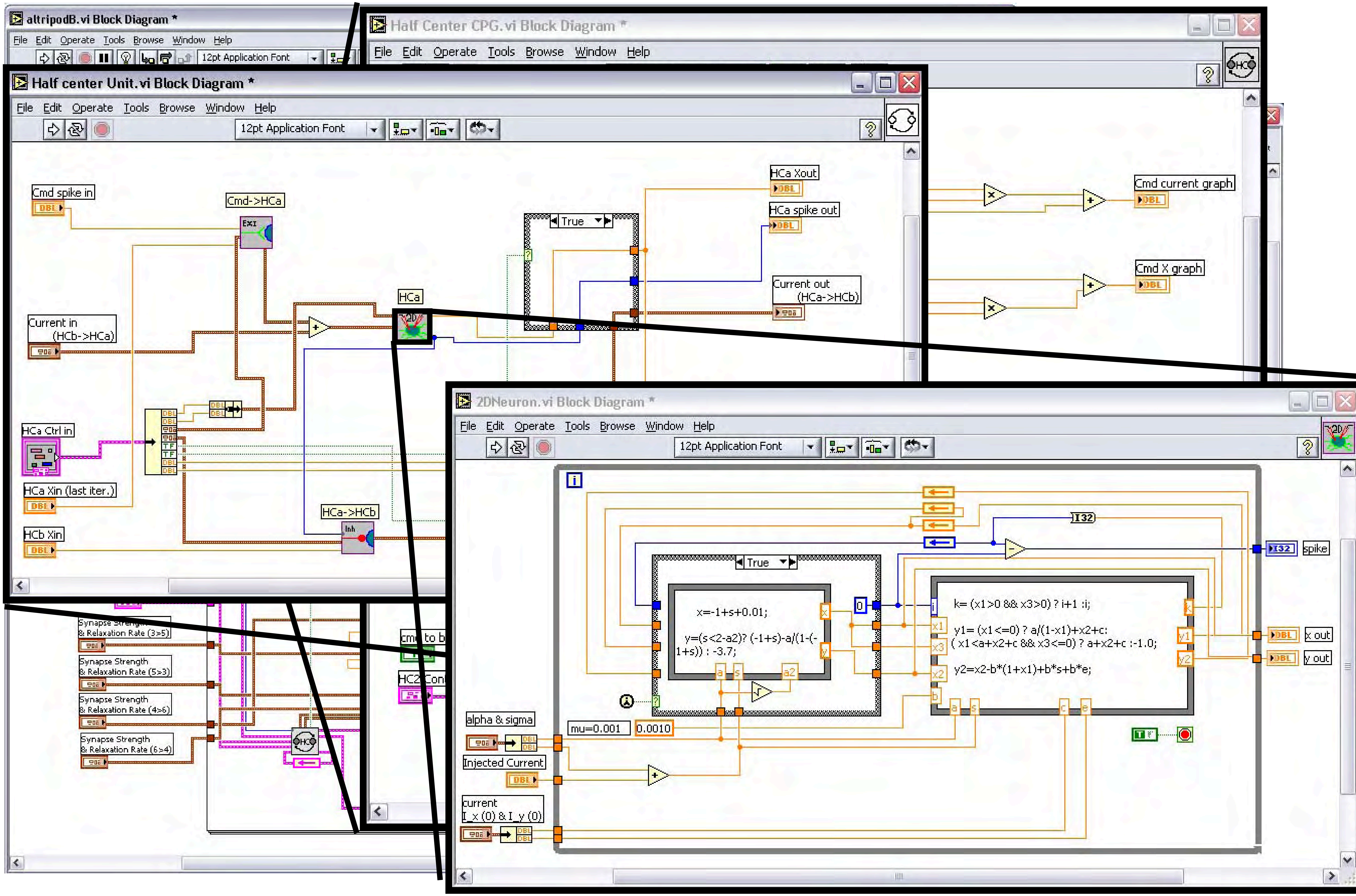
Working with map-based neurons



Working with map-based neurons



Working with map-based neurons



Synaptic Networks

Tunable Parameters

Synaptic Strength

Synaptic Time Constant

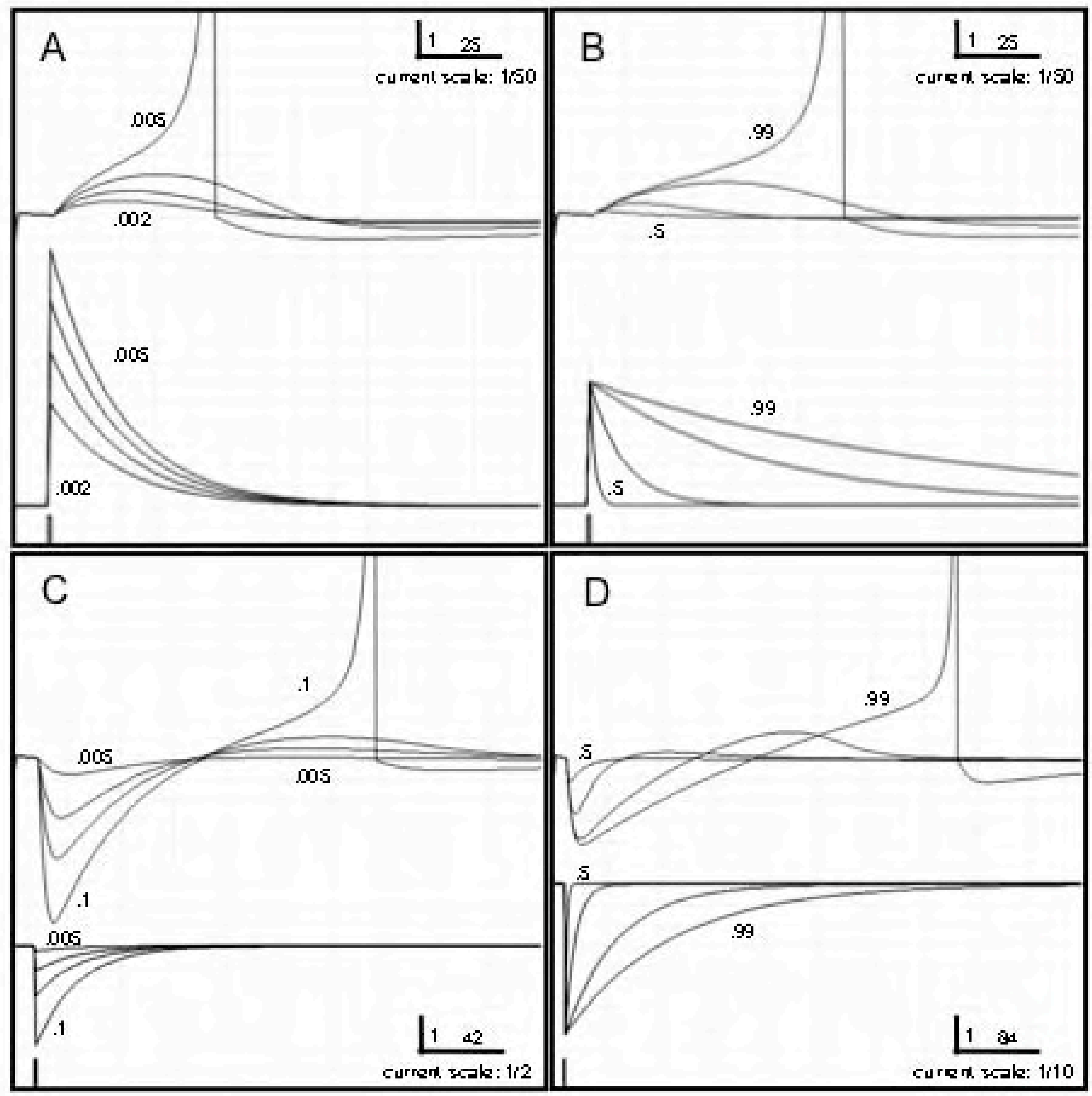
Excitatory Synapse

.002
.003
.004
.005

rr=0.95

.5
.9
.98
.99

st=0.002



Inhibitory Synapse

.005
.025
.05
.1

rr=0.95

.5
.9
.98
.99

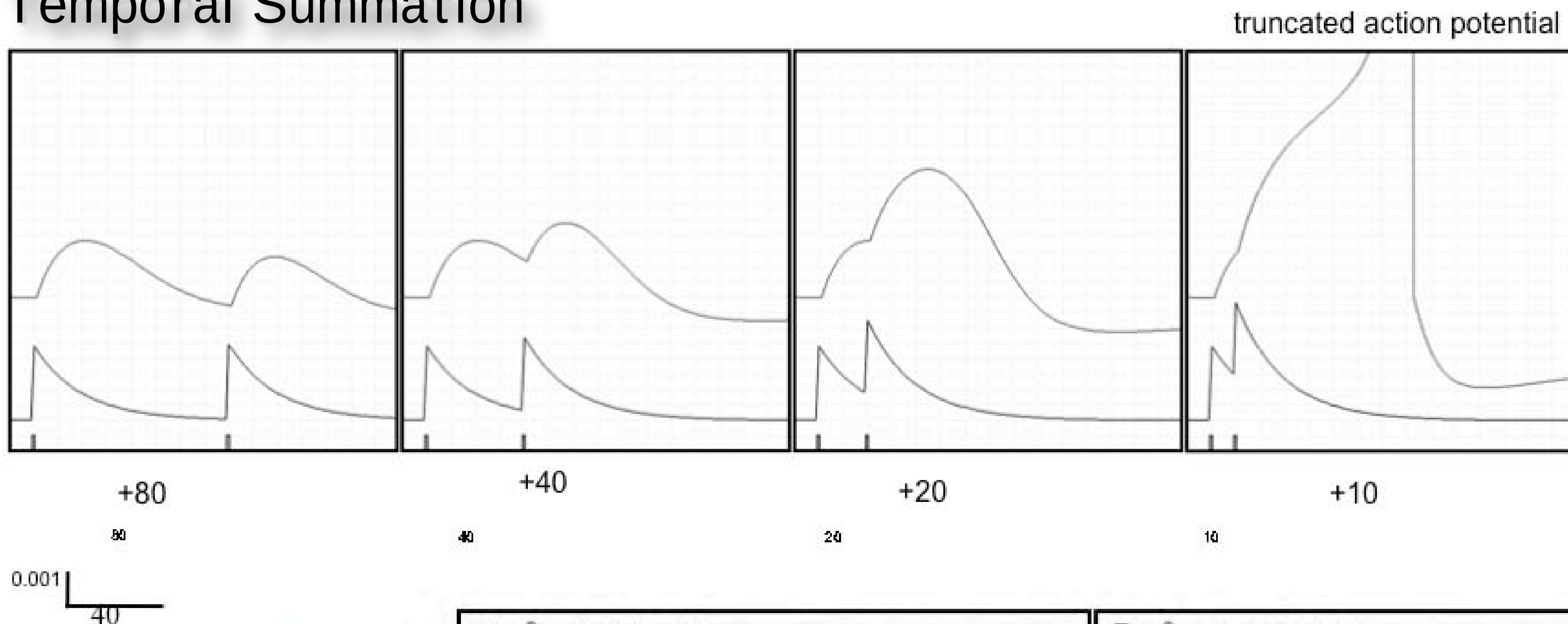
st=0.03

Dan Knudsen

Synaptic Networks

Integration

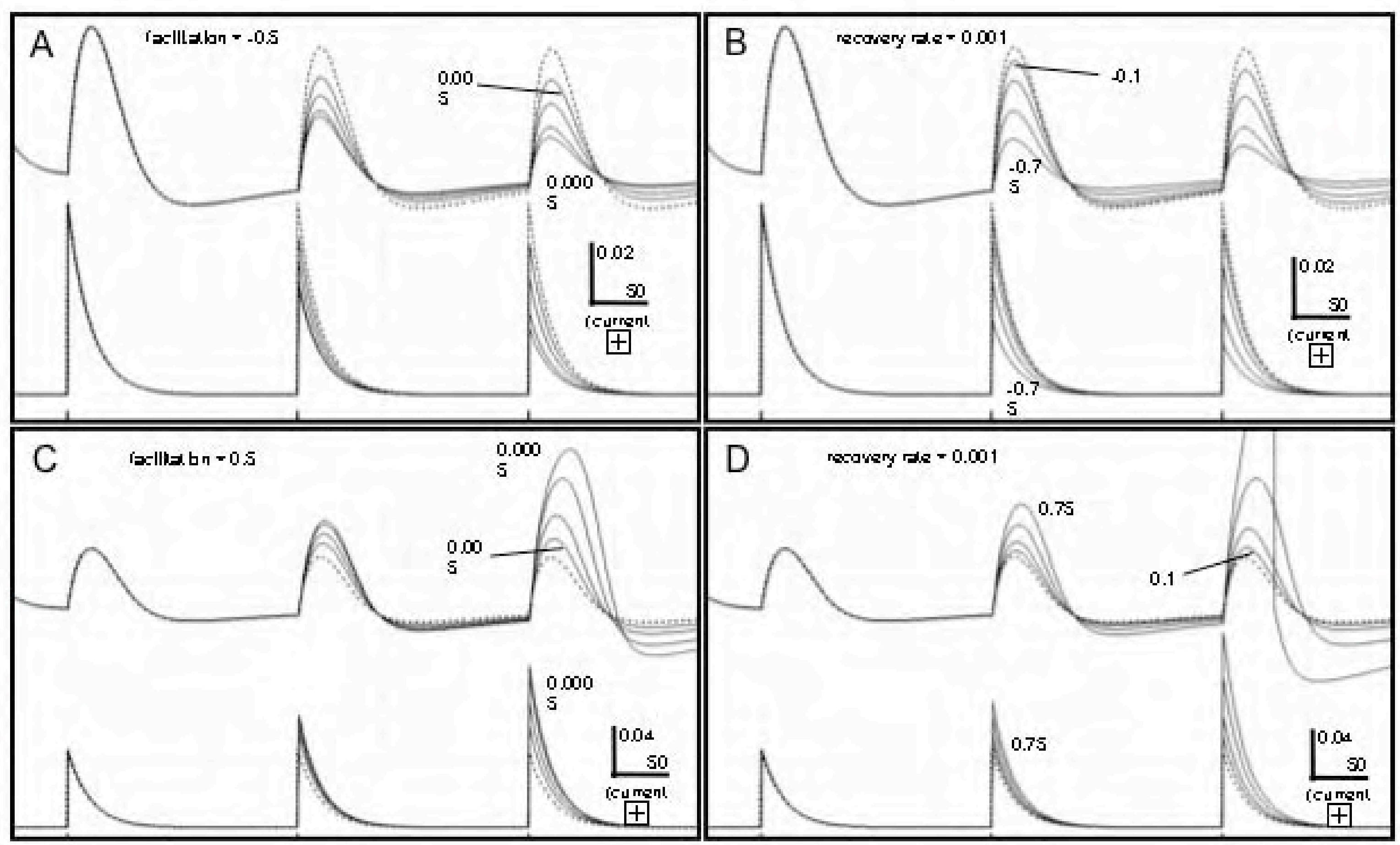
Temporal Summation



Plasticity

Antifacilitation

facil= -0.5
vary recov:
.0005
.001
.0025
.005



recov= .001
vary facil:
-.1
-.25
-.5
-.75

Facilitation

facil= 0.5
vary recov:
.0005
.001
.0025
.005

recov= .001
vary facil:
.1
.25
.5
.75

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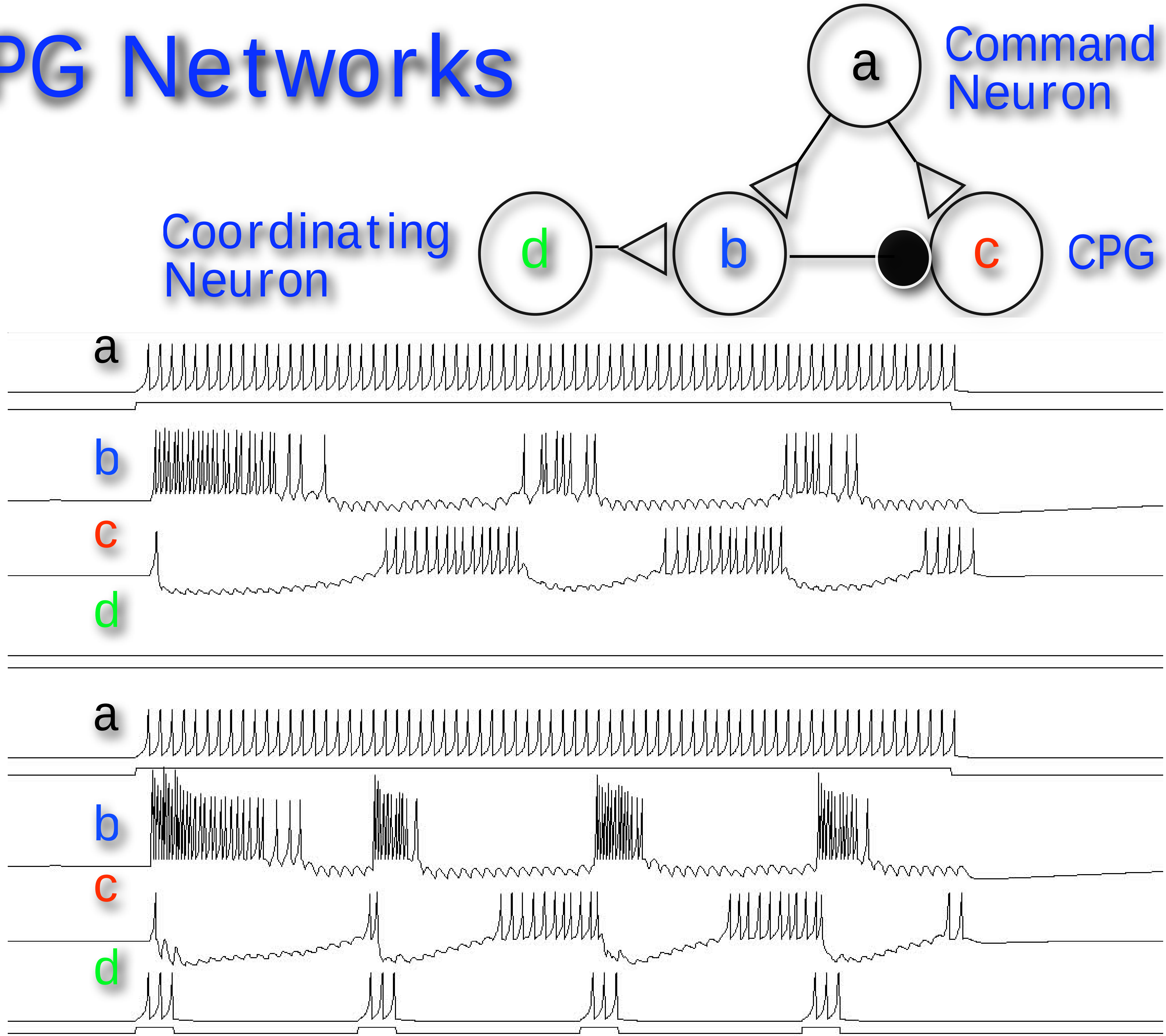
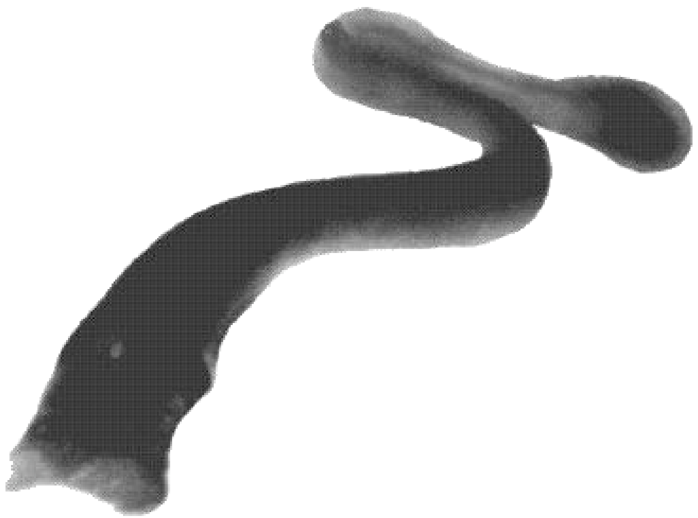
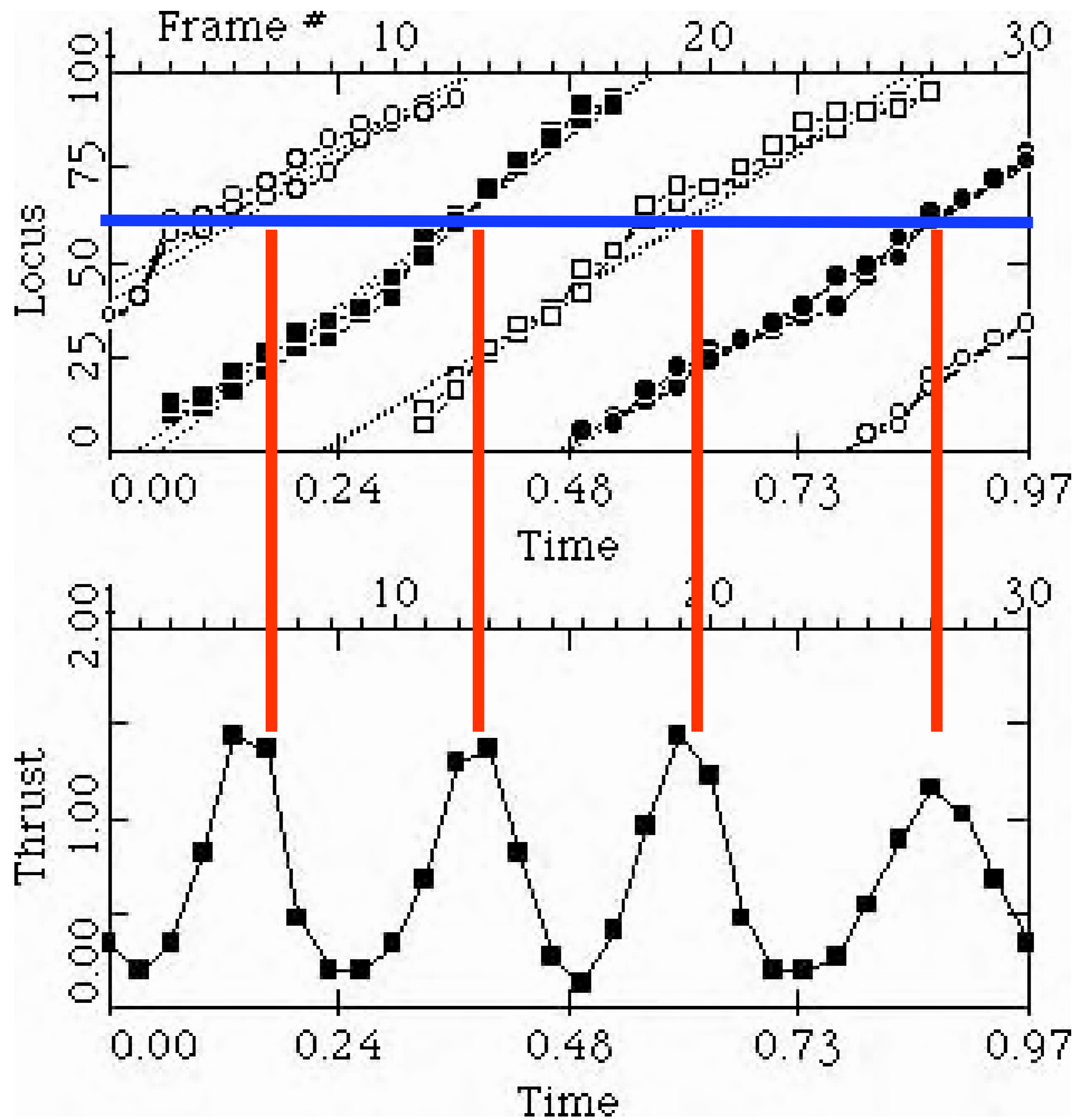
CPG Networks



Thrust Generation



- Swim cycle organized into flexion waves
- One peak of thrust per flexion wave



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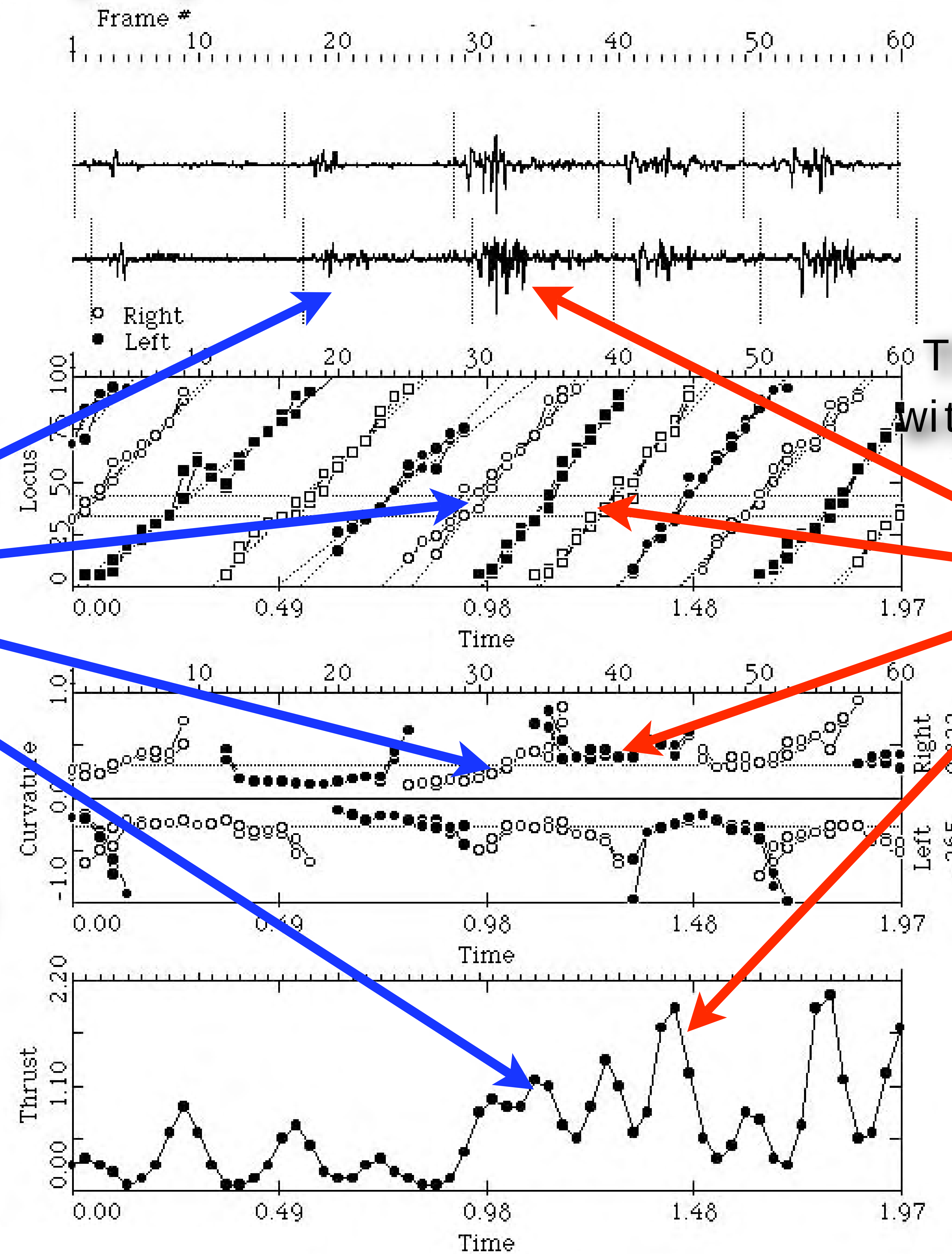
Electromyography



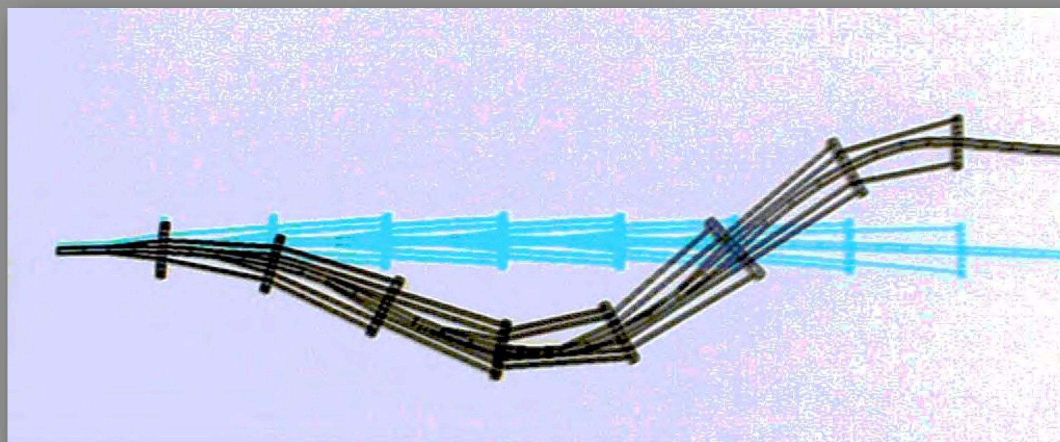
Thrust correlated with EMG Amplitude

Big Lag between EMG and Flexion

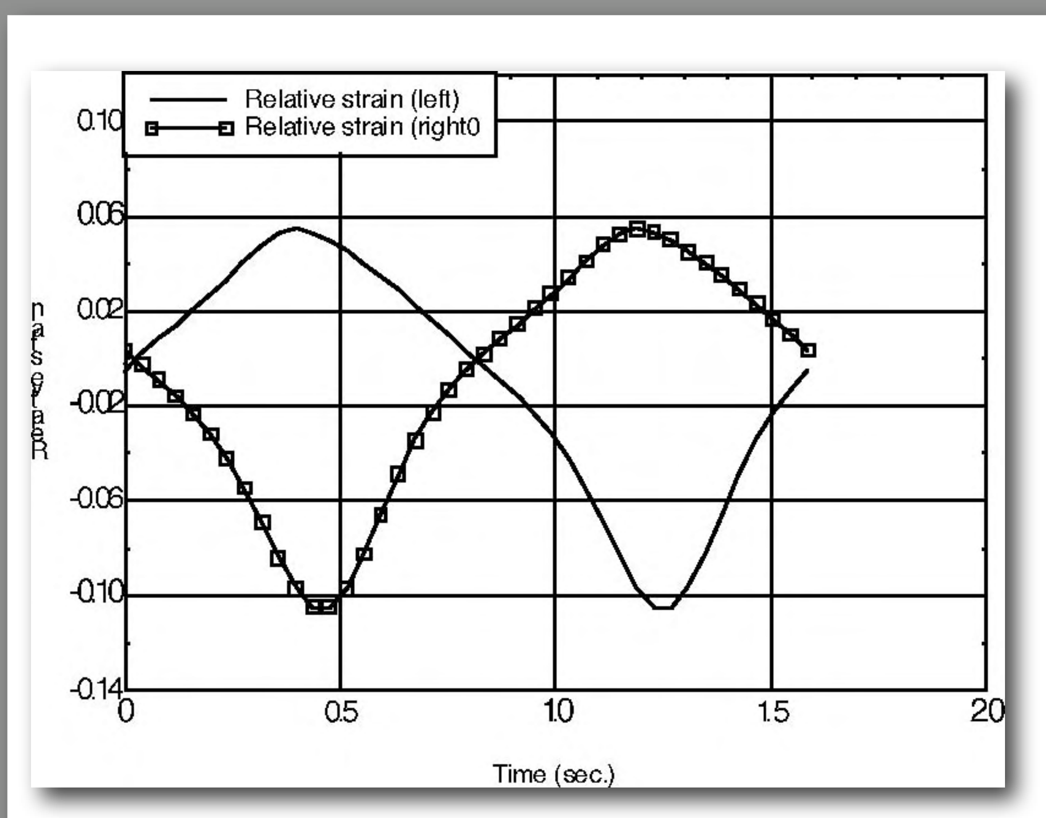
- No chance for movement related feedback to modulate the control signal
- Proprioceptive reflexes irrelevant

Mechanodynamic Model

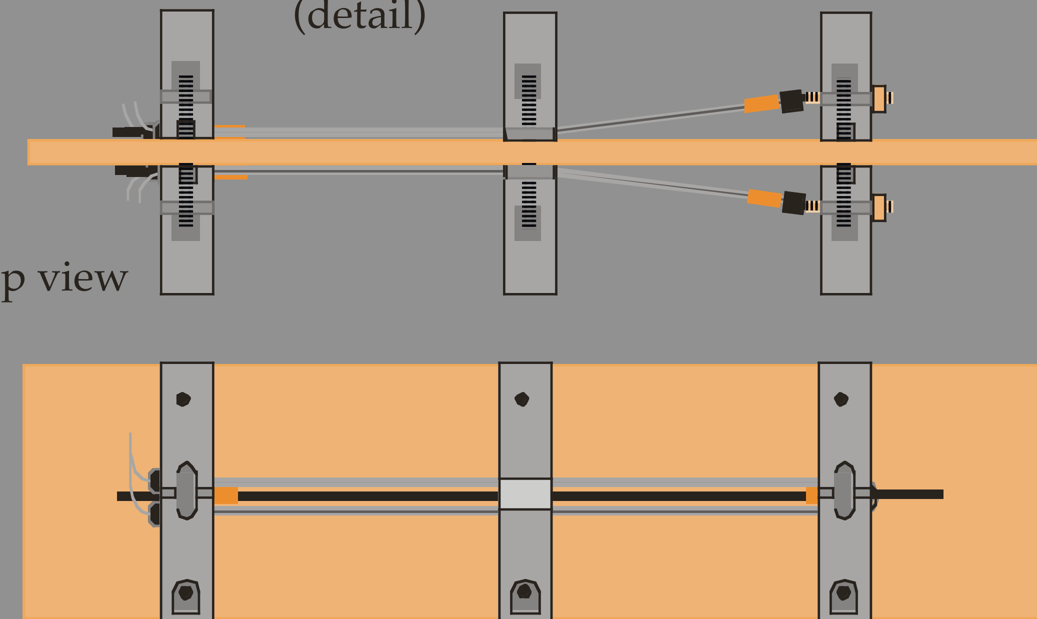
Finite Element Model



Calculated Strains

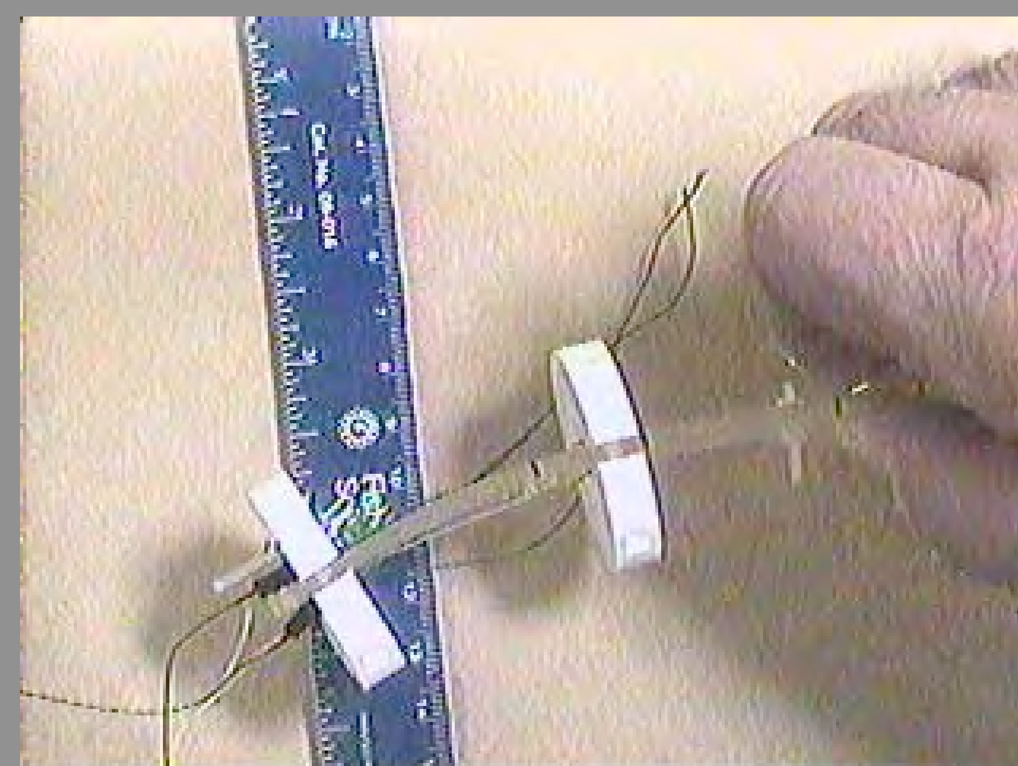


Undulation Module
(detail)

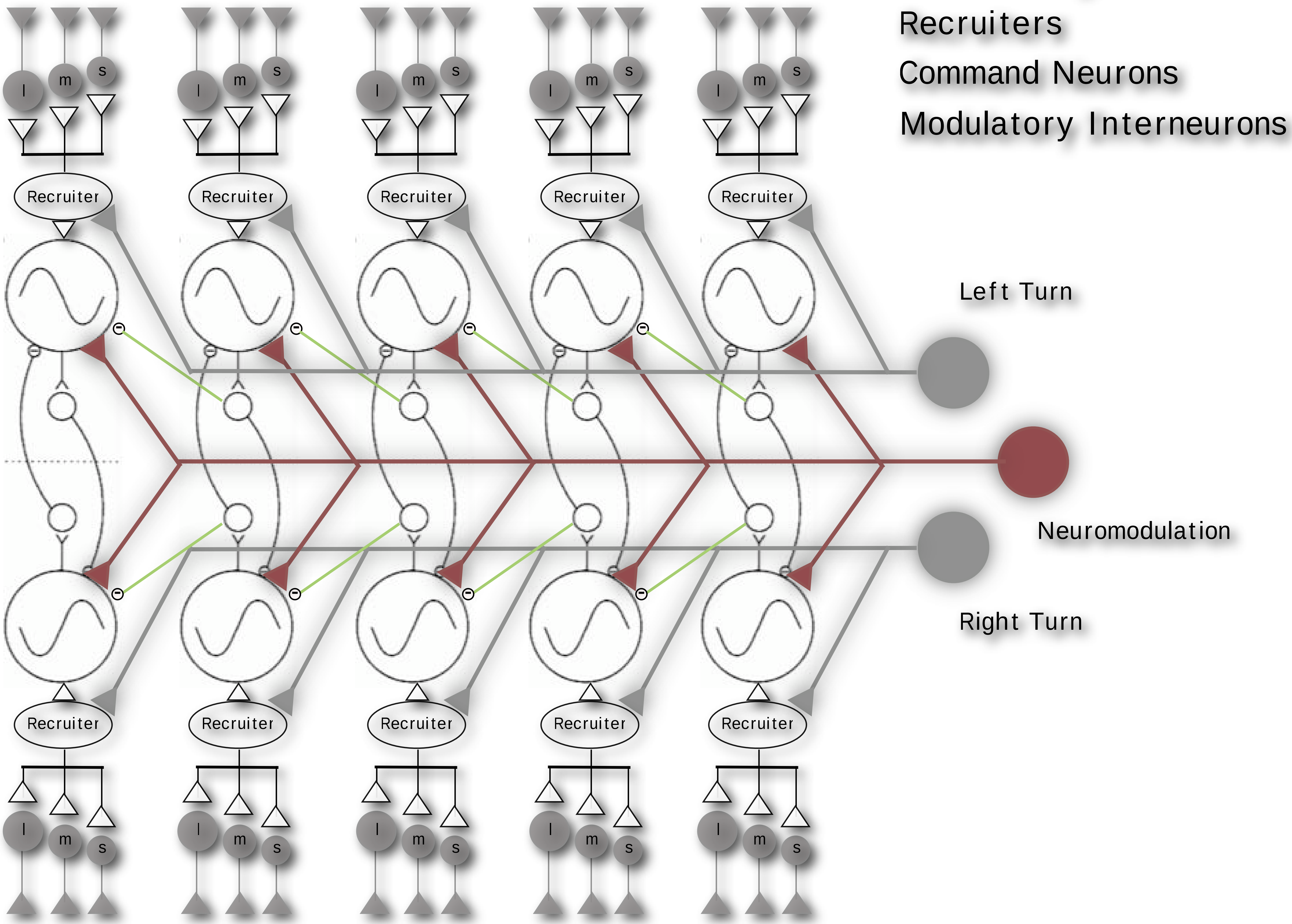


top view

side view



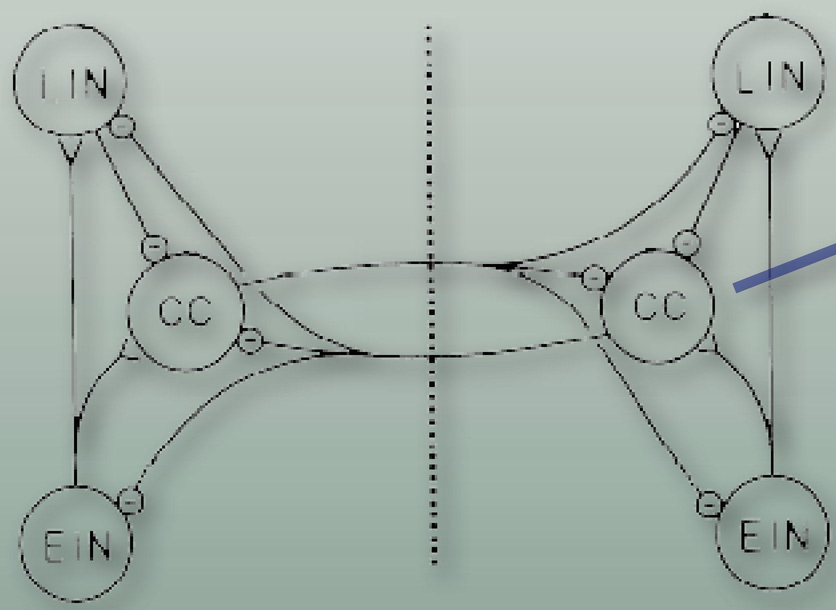
Lamprey CPG

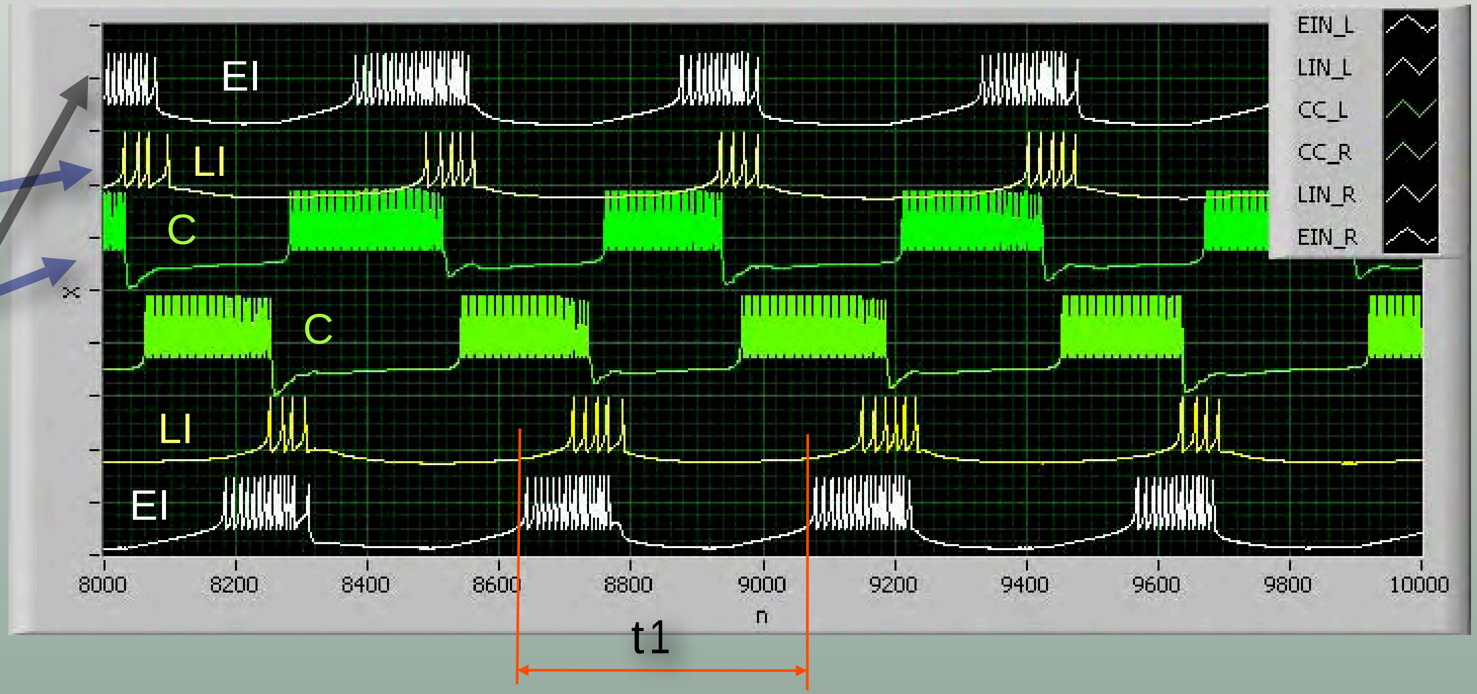


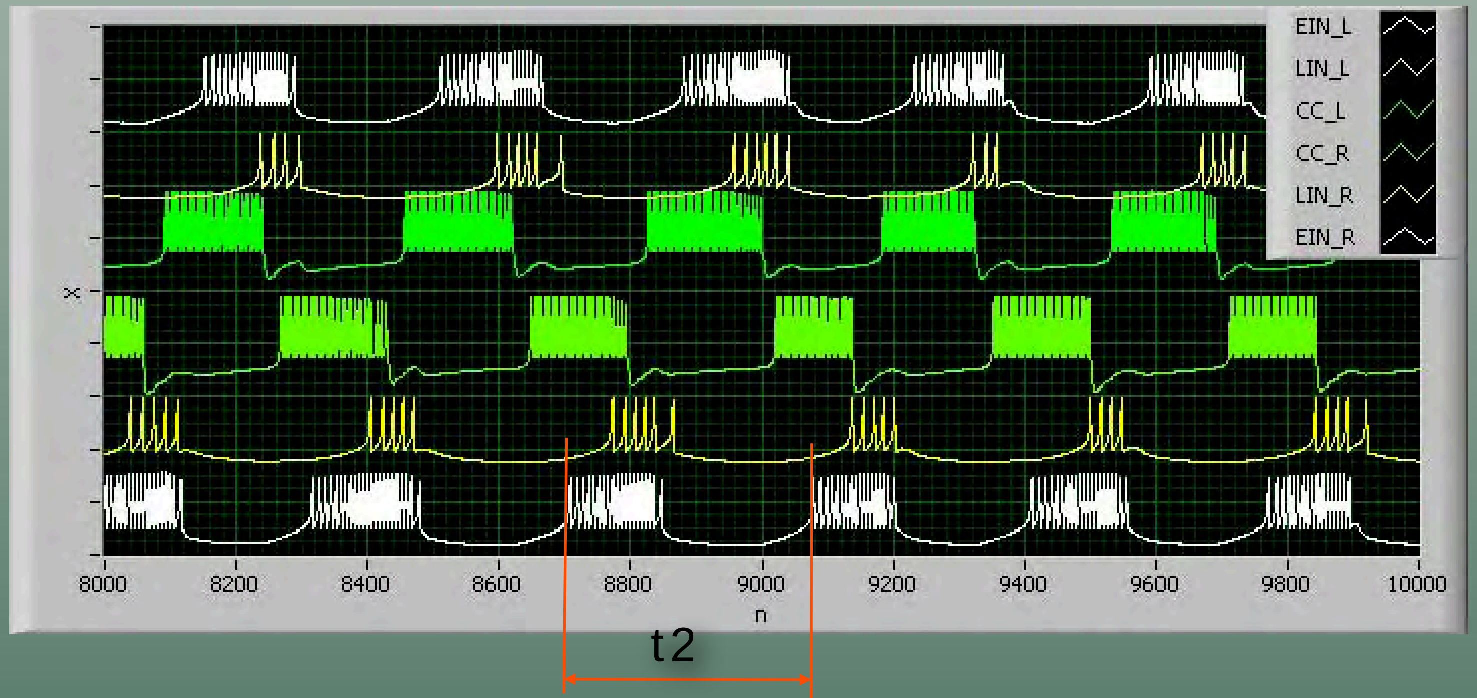
Central Pattern Generators
Coordinating Neurons
Recruiters
Command Neurons
Modulatory Interneurons
Recruiter
l
m
s
Left Turn
Neuromodulation
Right Turn

Segmental CPG

- Excitation level of EINs controls the frequency of bursting







EIN – Excitatory Interneurons,
CC – Inhibitory Commissural Interneurons,
LIN – Lateral Interneurons

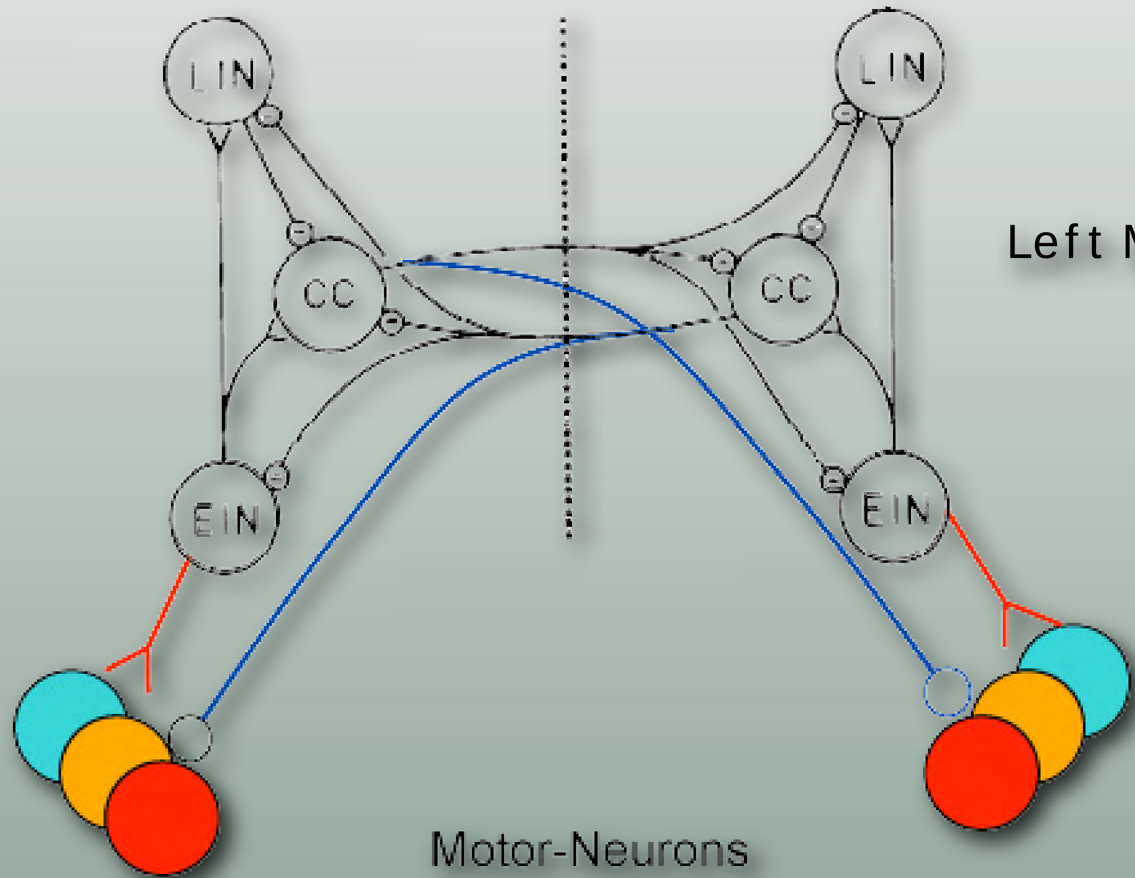
- Inhibitory Synapse

- Excitatory Synapse

J.T. Buchanan, Progress in Neurobiology, 63, (2001) 441

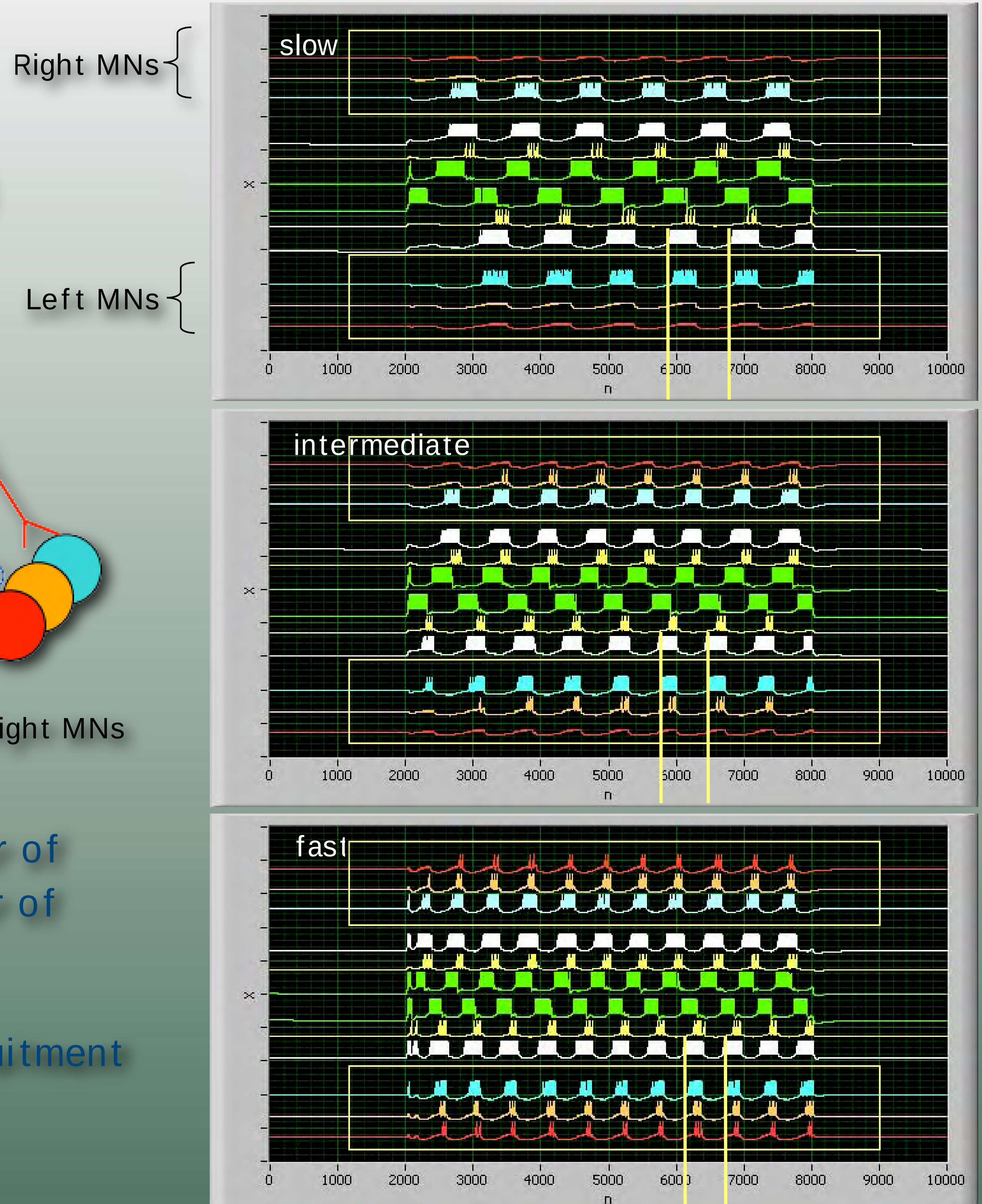
t2<t1

Recruiters



Left MNs

Right MNs

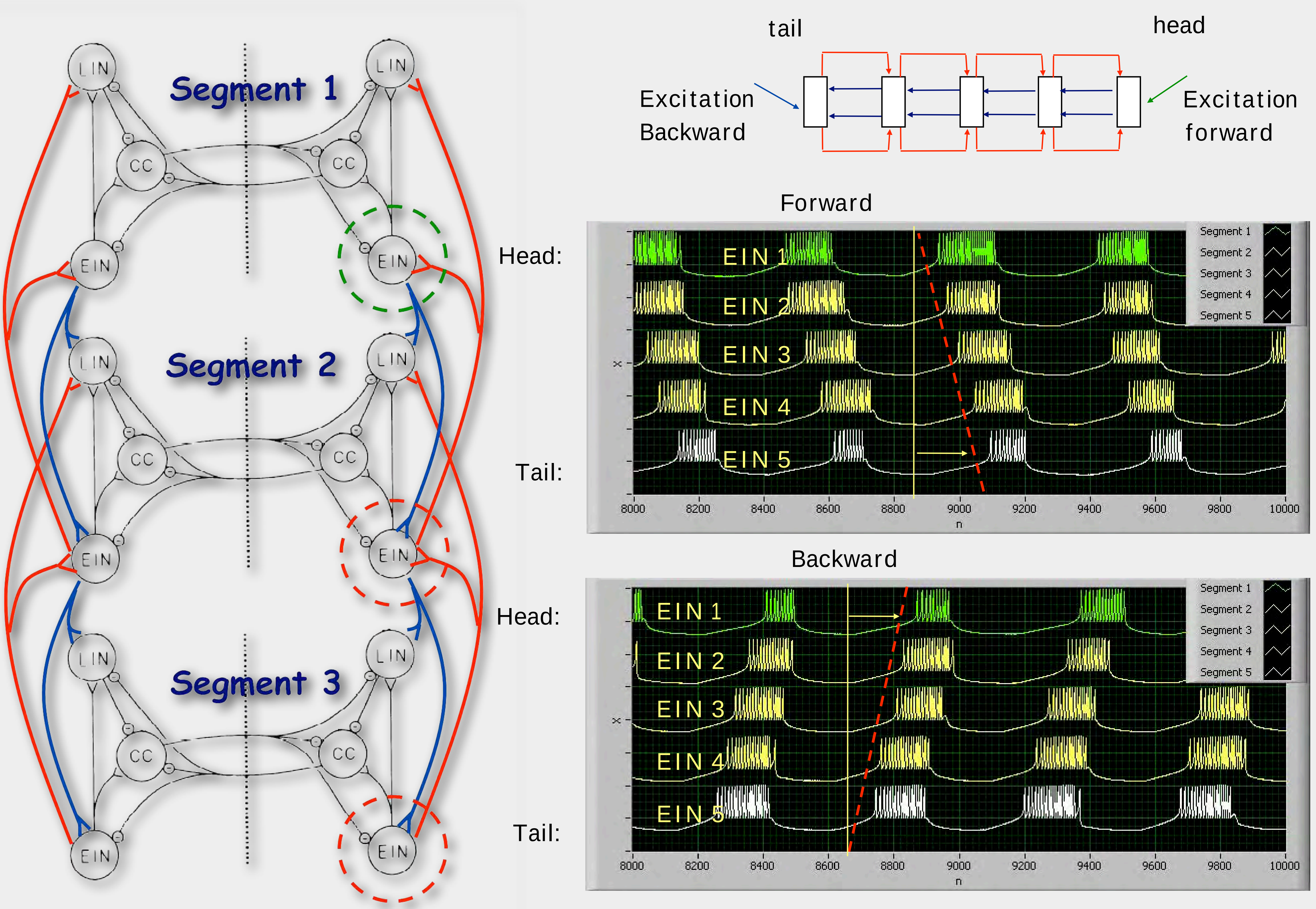


Hennimen Size Principle:

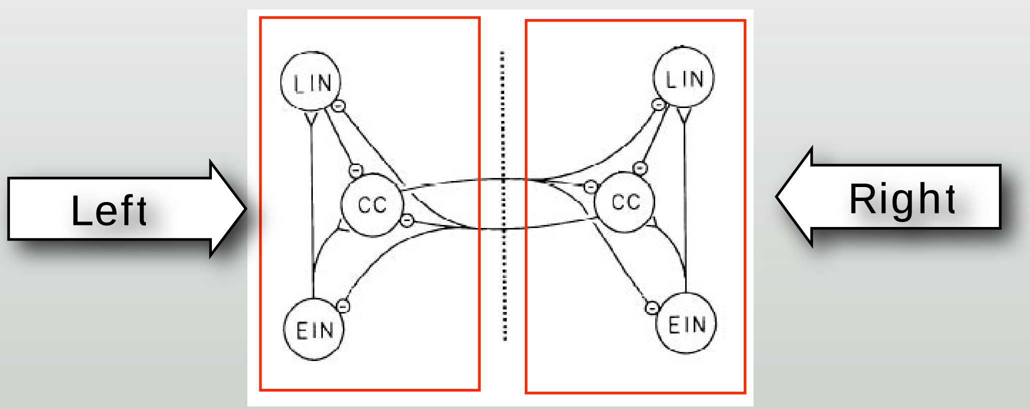
Motor units are recruited in order of size which determines the number of muscle fibers they activate.

Muscular force is graded by recruitment of larger motor units.

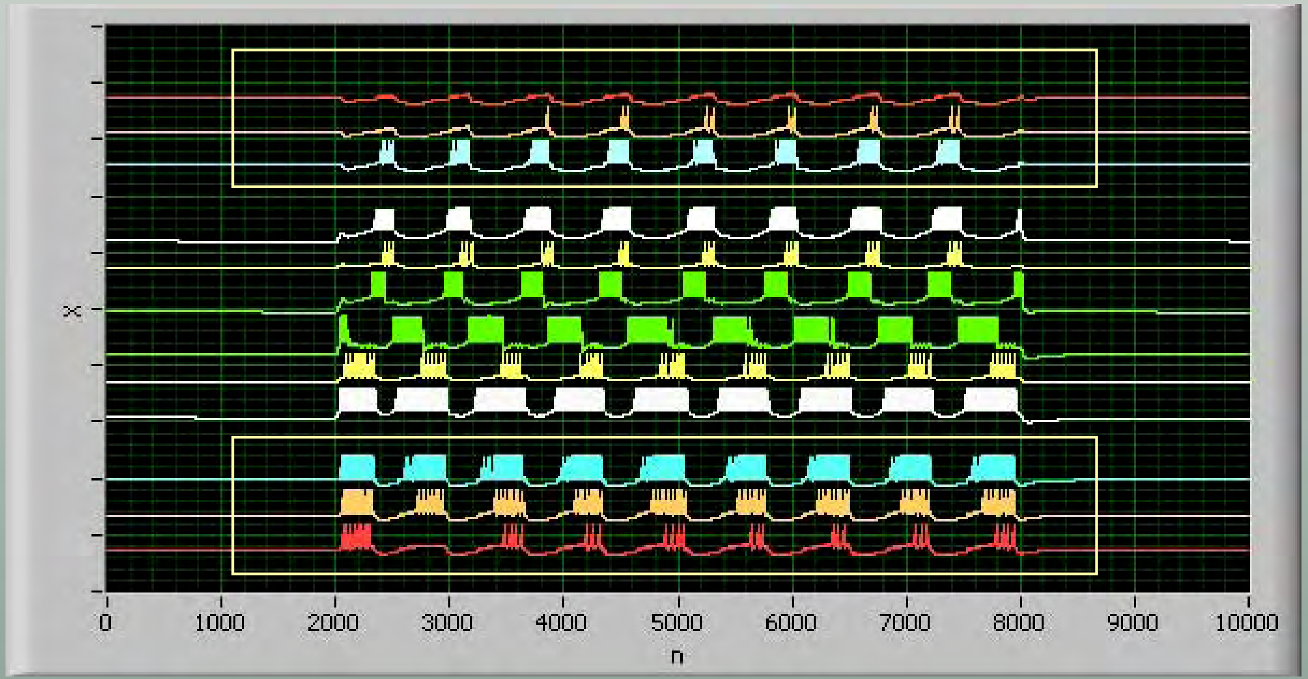
Intersegmental Coordination



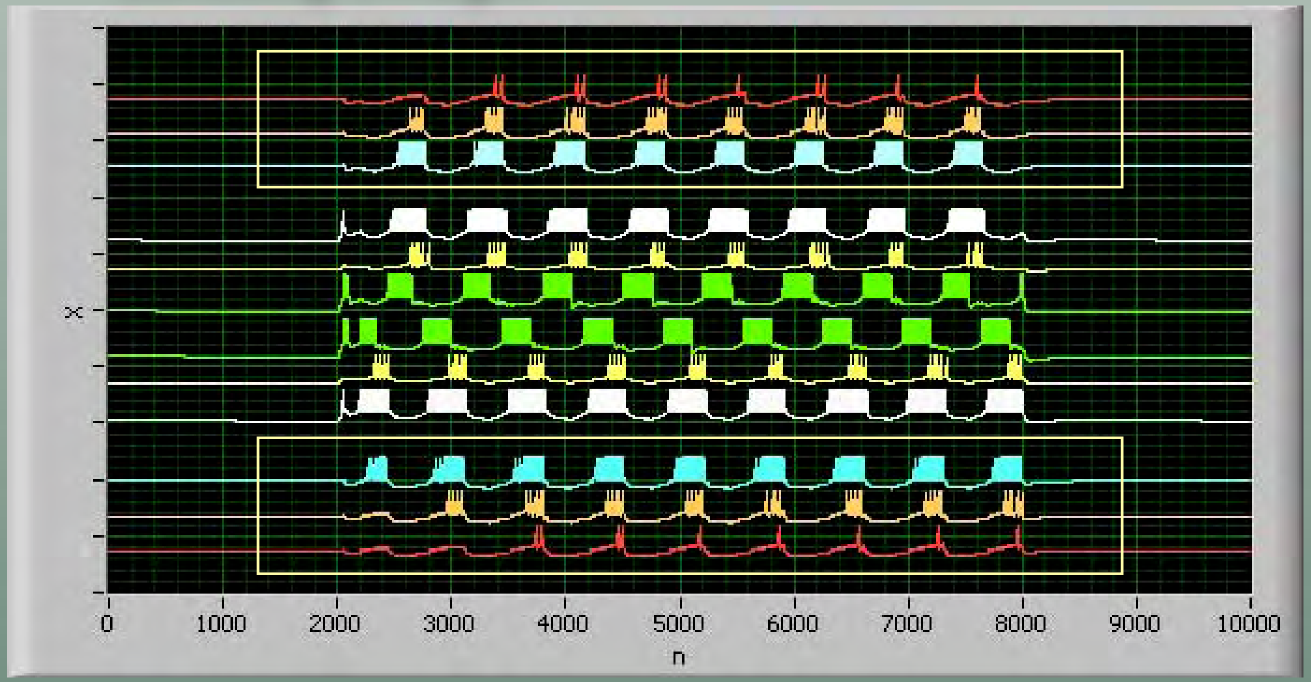
Turning: Recruitment

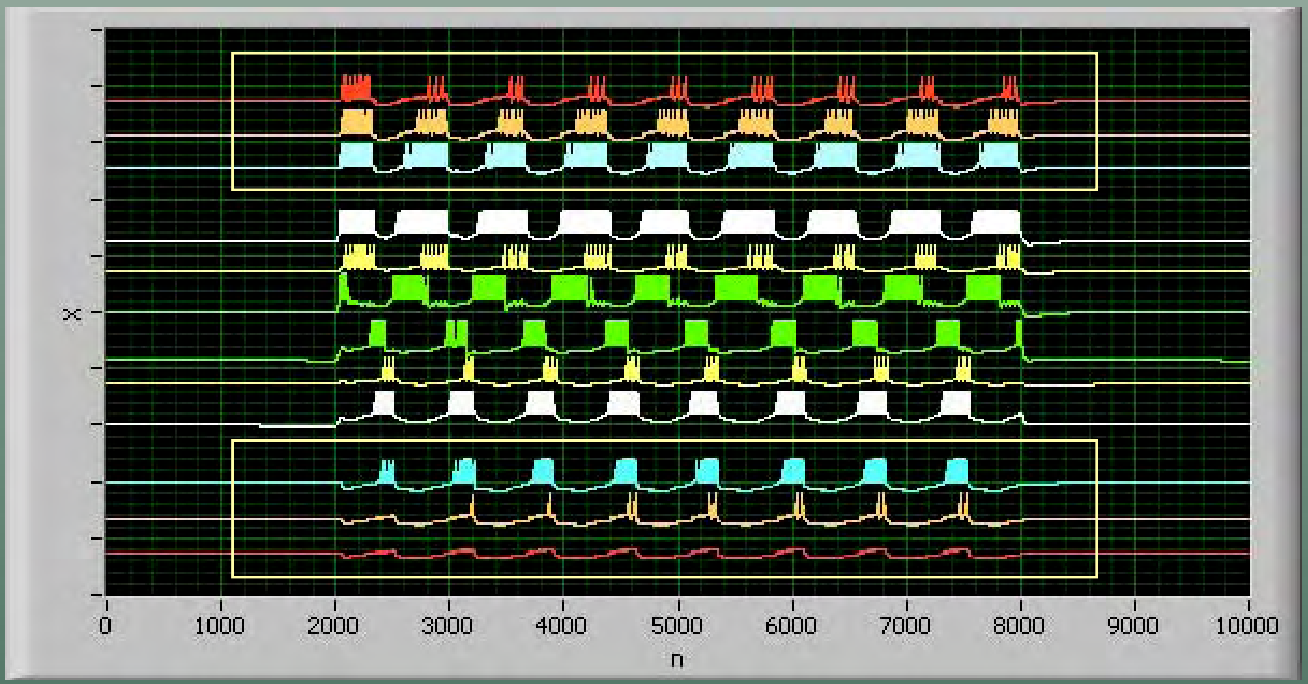


Turning Left



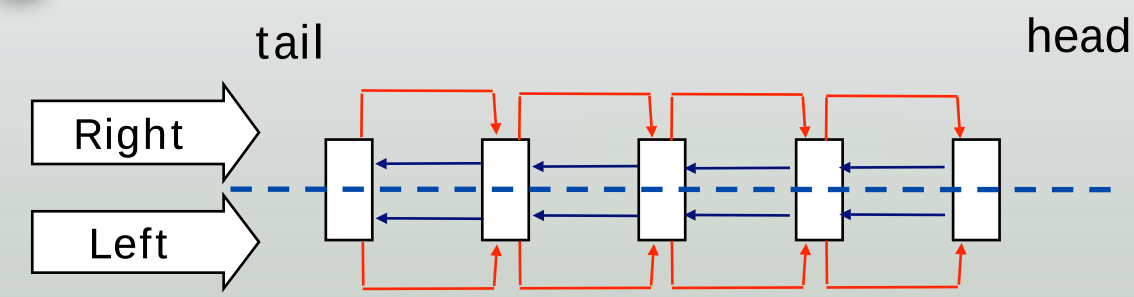
Swimming Straight



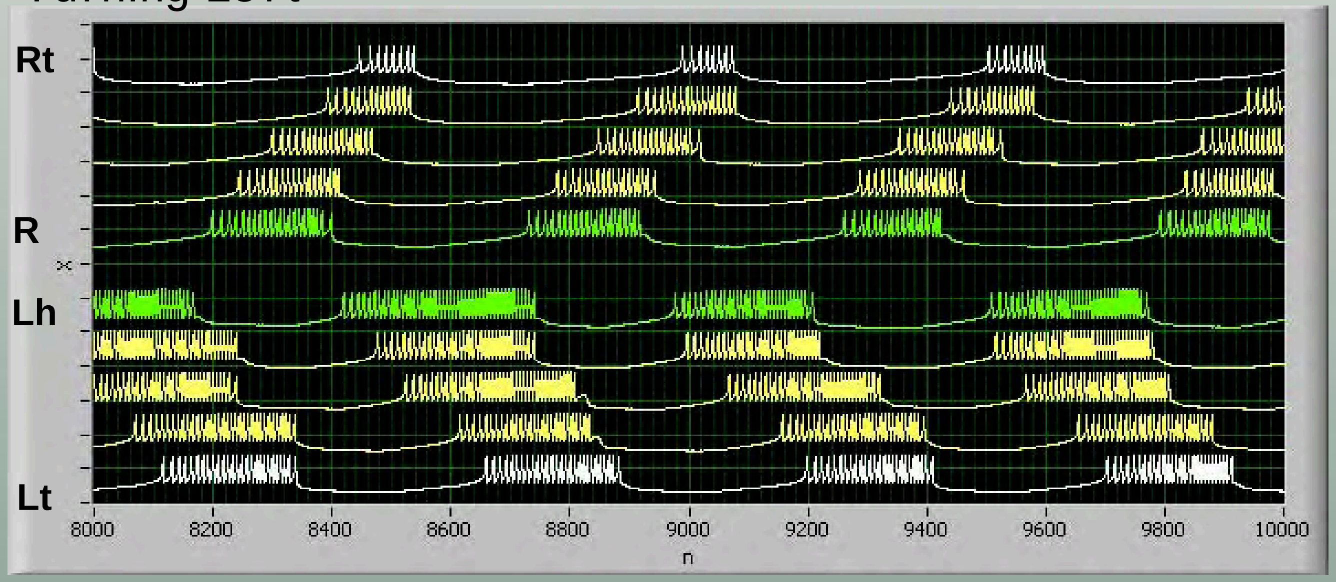


Turning Right

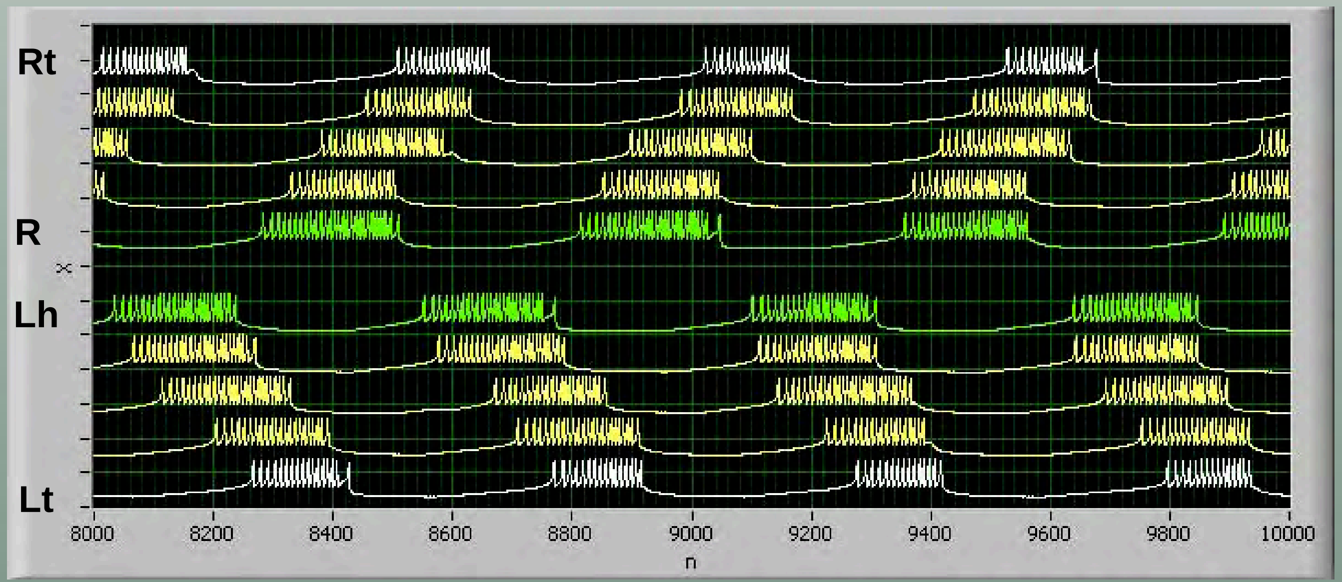
Multi-Segmental Turning



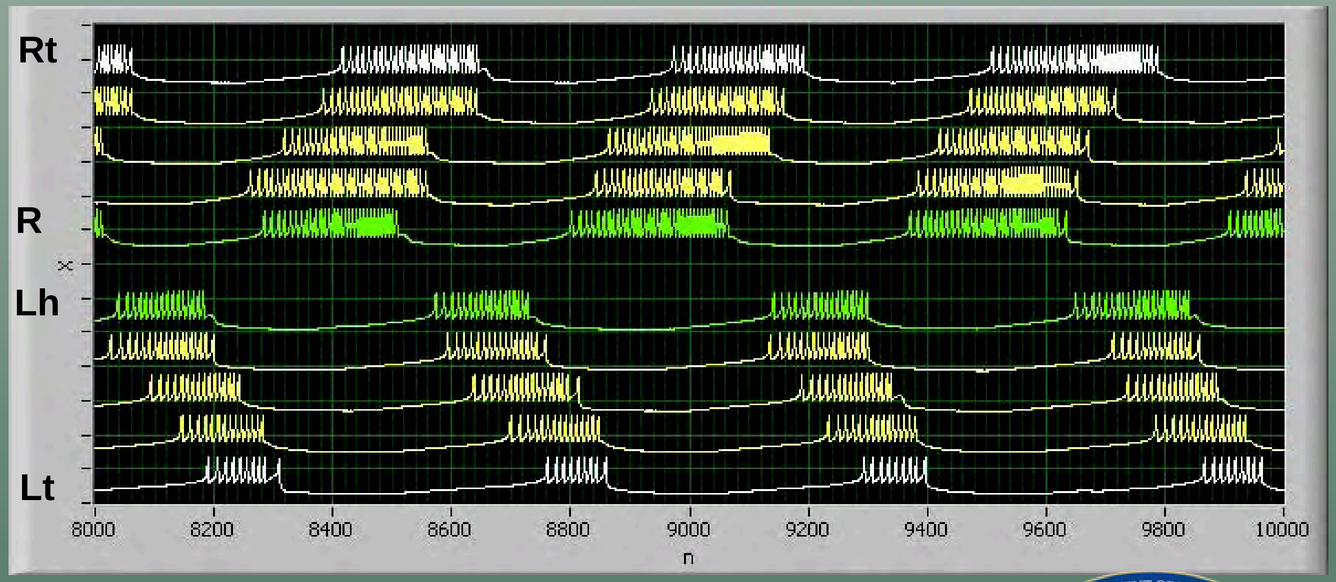
Turning Left



Straight Forward Swimming

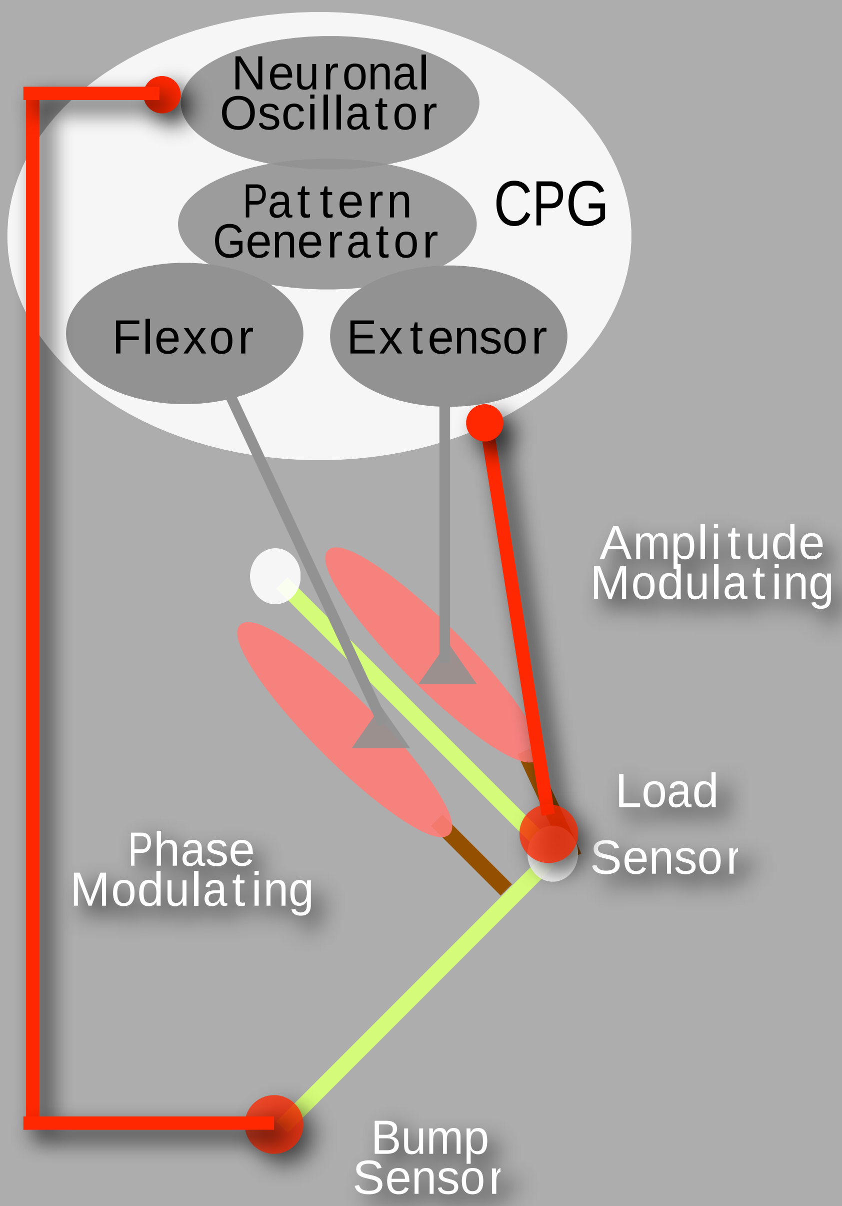


Turning Right



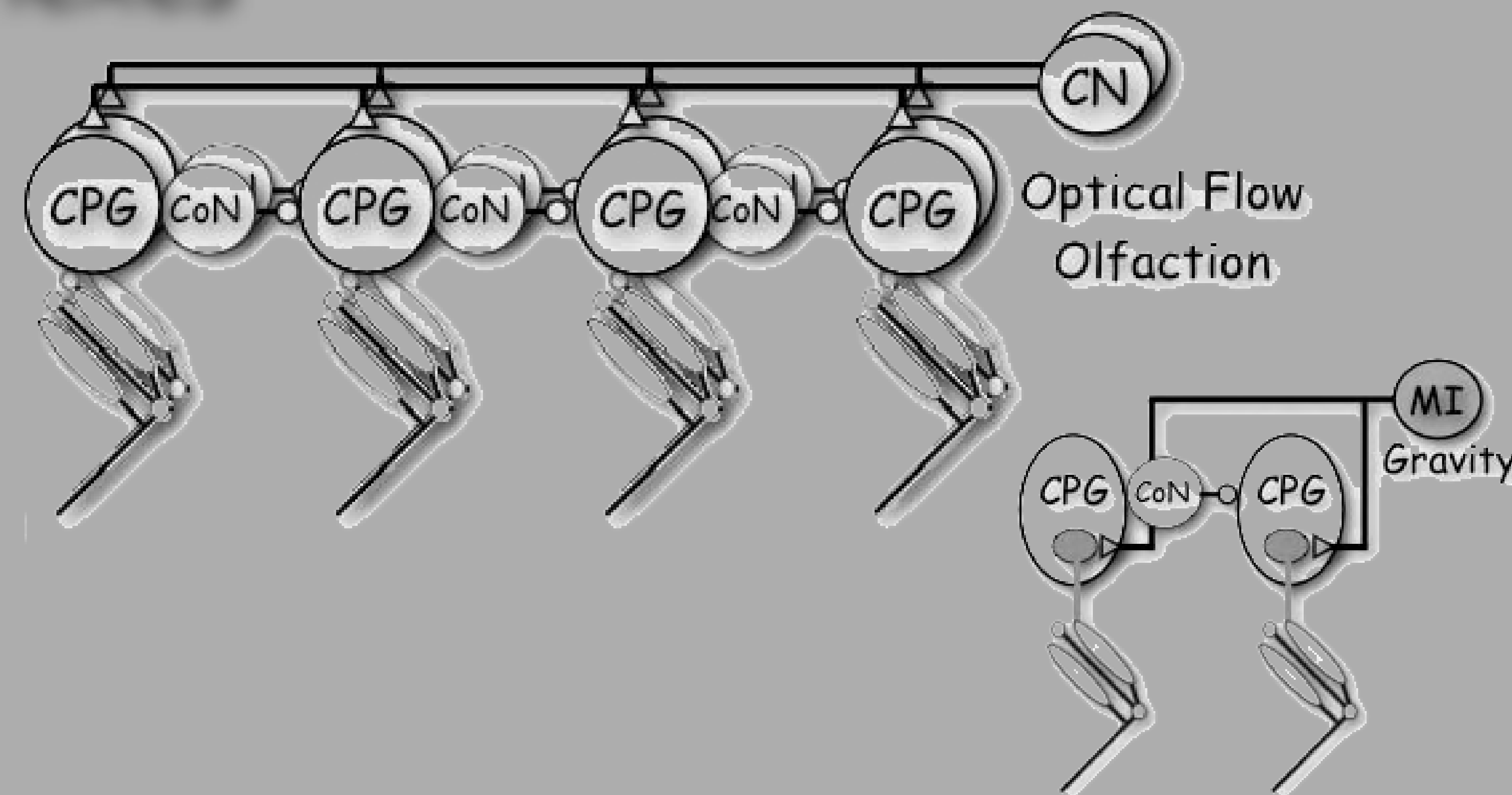
Sensory Feedback

Proprioceptive Reflexes



Irrelevant due to long mechanical lags between excitation and movement!

Exteroceptive Reflexes

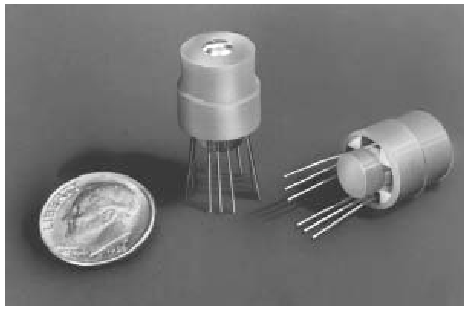


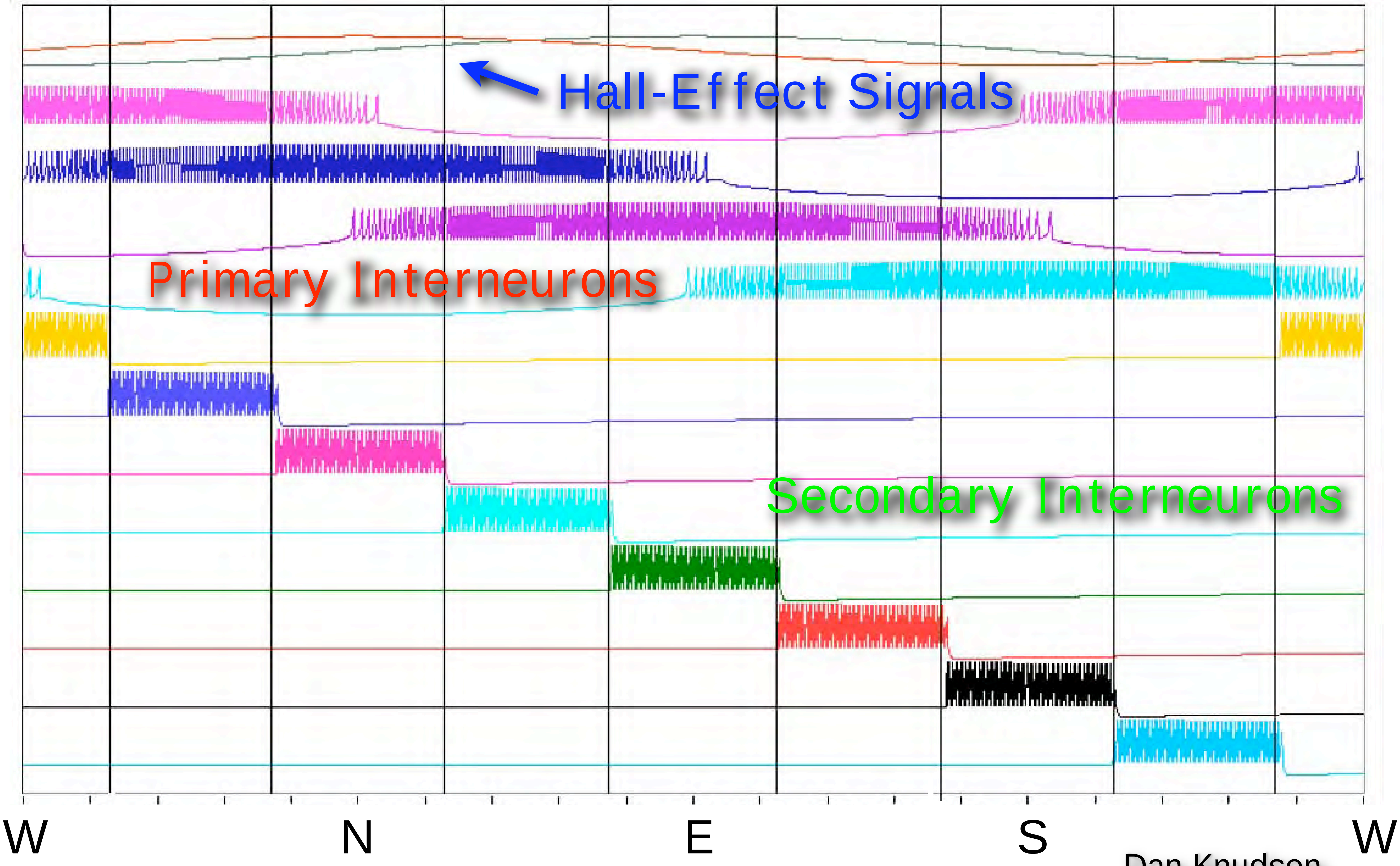
Amplitude Modulating: Control number, size and discharge frequency of motor neurons. Operate on motor neurons.

Phase Modulating: Reset timing of CPGs. Operate on neuronal oscillators.

Exteroceptive: Modulate sets of CPGs. Operate through command and modulatory interneurons

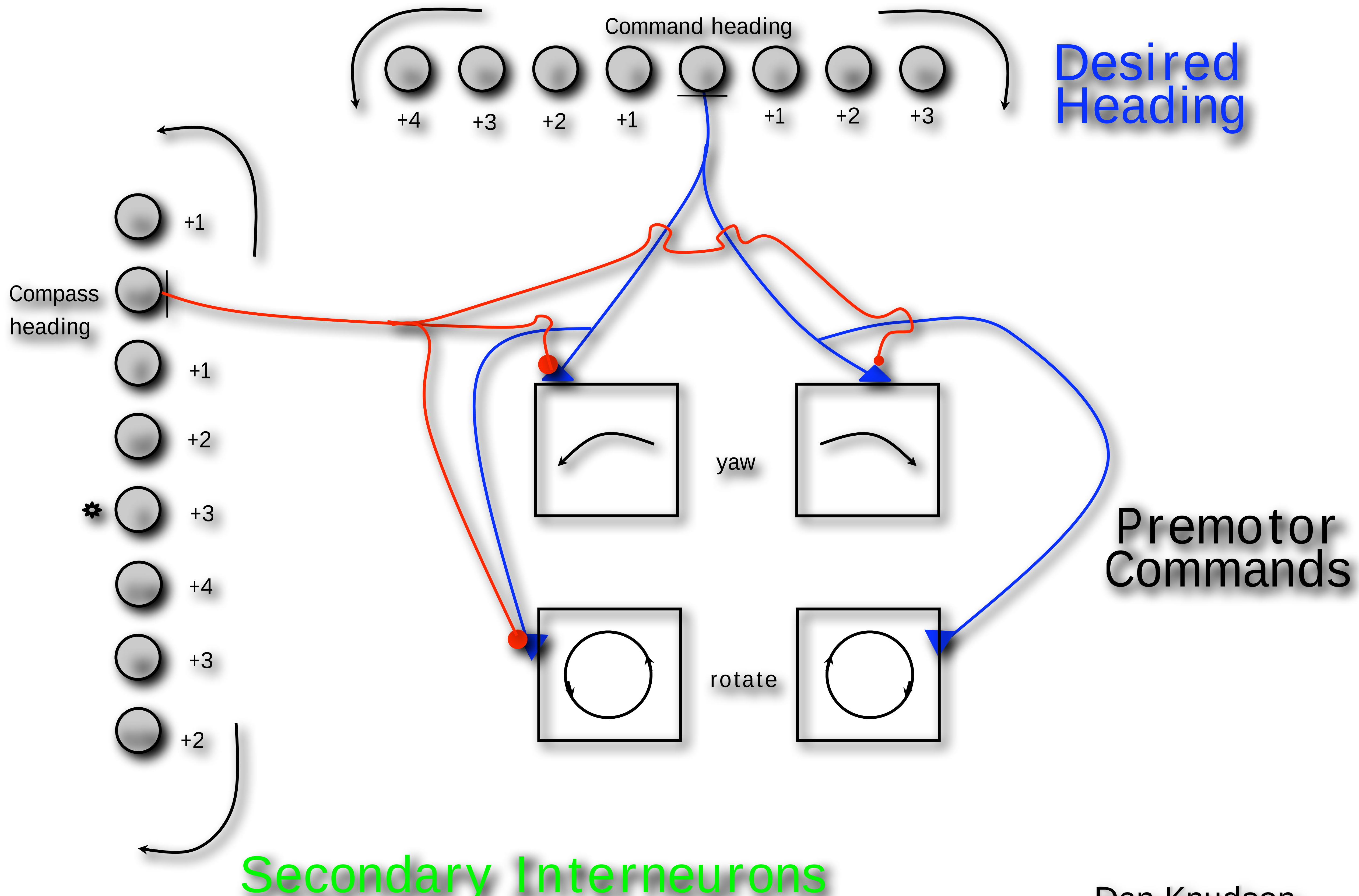
Neuronal Compass





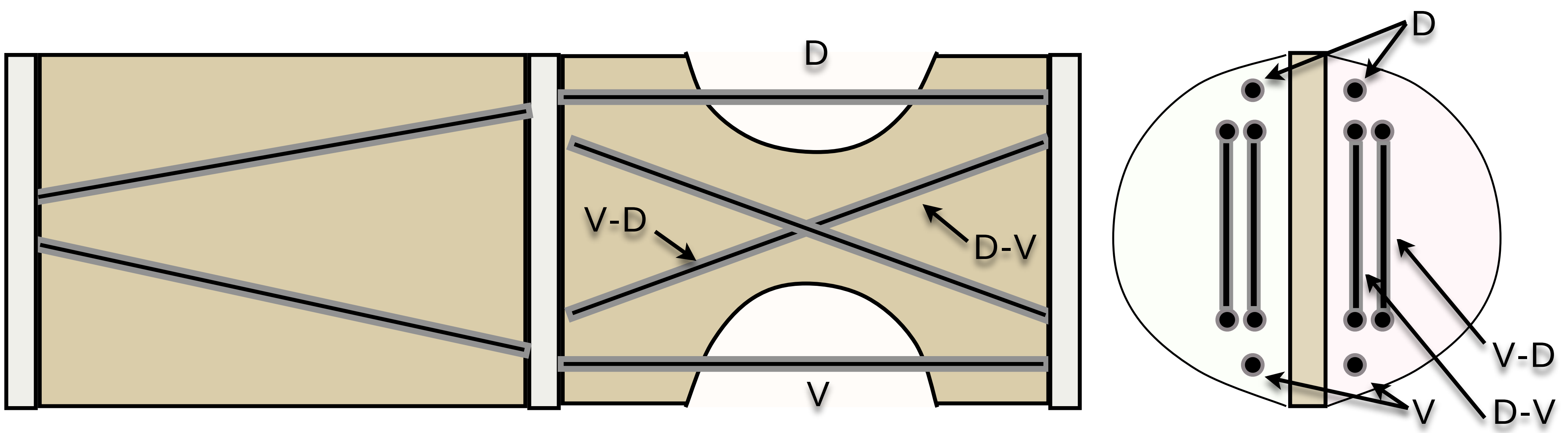
Dan Knudsen

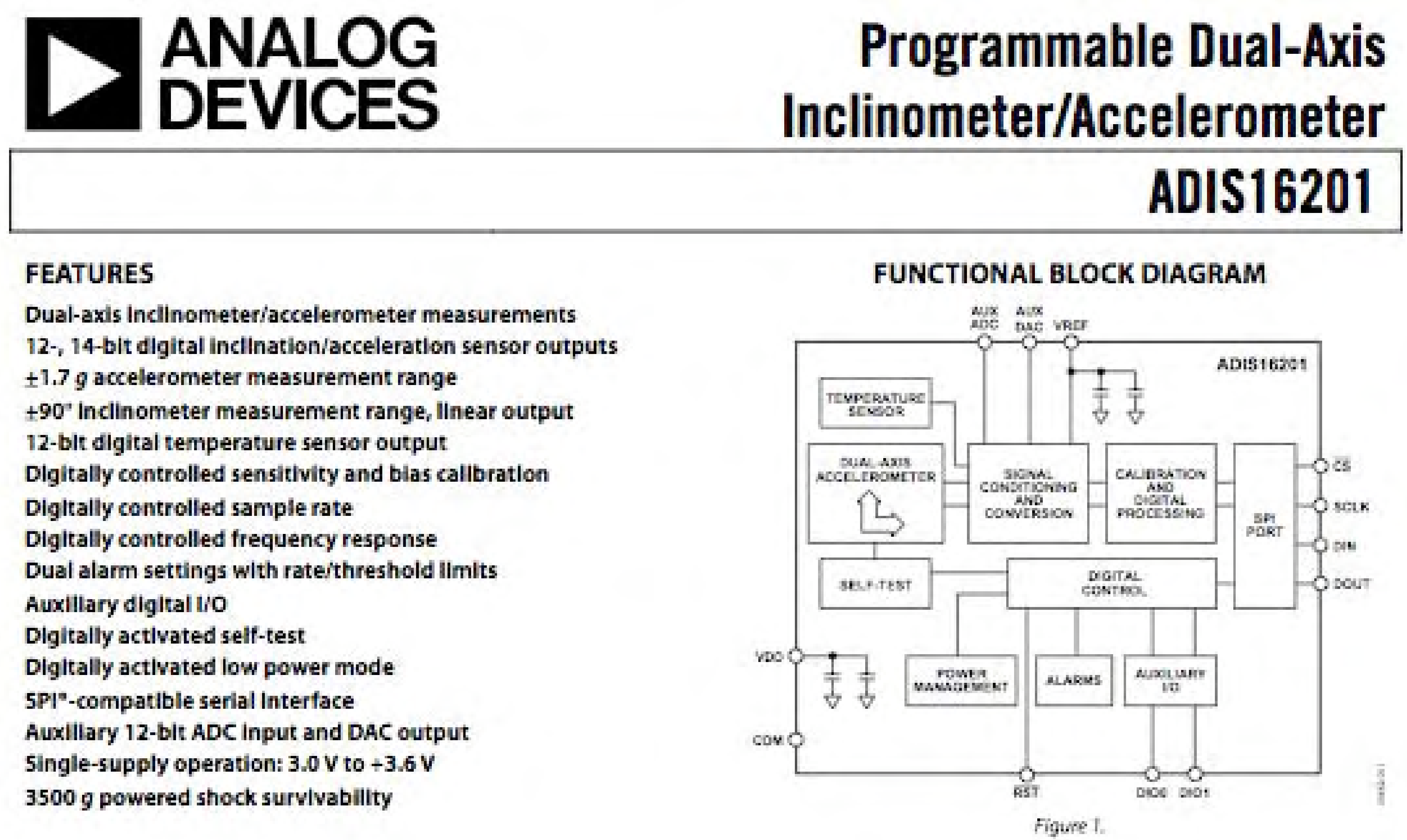
Neuronal Compass



Dan Knudsen

Pitch and Roll Layer





ANALOG DEVICES

Programmable Dual-Axis Inclinometer/Accelerometer

ADIS16201

FEATURES

Dual-axis inclinometer/accelerometer measurements
12-, 14-bit digital inclination/acceleration sensor outputs
±1.7 *g* accelerometer measurement range
±90° inclinometer measurement range, linear output
12-bit digital temperature sensor output
Digitally controlled sensitivity and bias calibration
Digitally controlled sample rate
Digitally controlled frequency response
Dual alarm settings with rate/threshold limits
Auxiliary digital I/O
Digitally activated self-test
Digitally activated low power mode
SPI®-compatible serial interface
Auxiliary 12-bit ADC input and DAC output
Single-supply operation: 3.0 V to +3.6 V
3500 *g* powered shock survivability

FUNCTIONAL BLOCK DIAGRAM

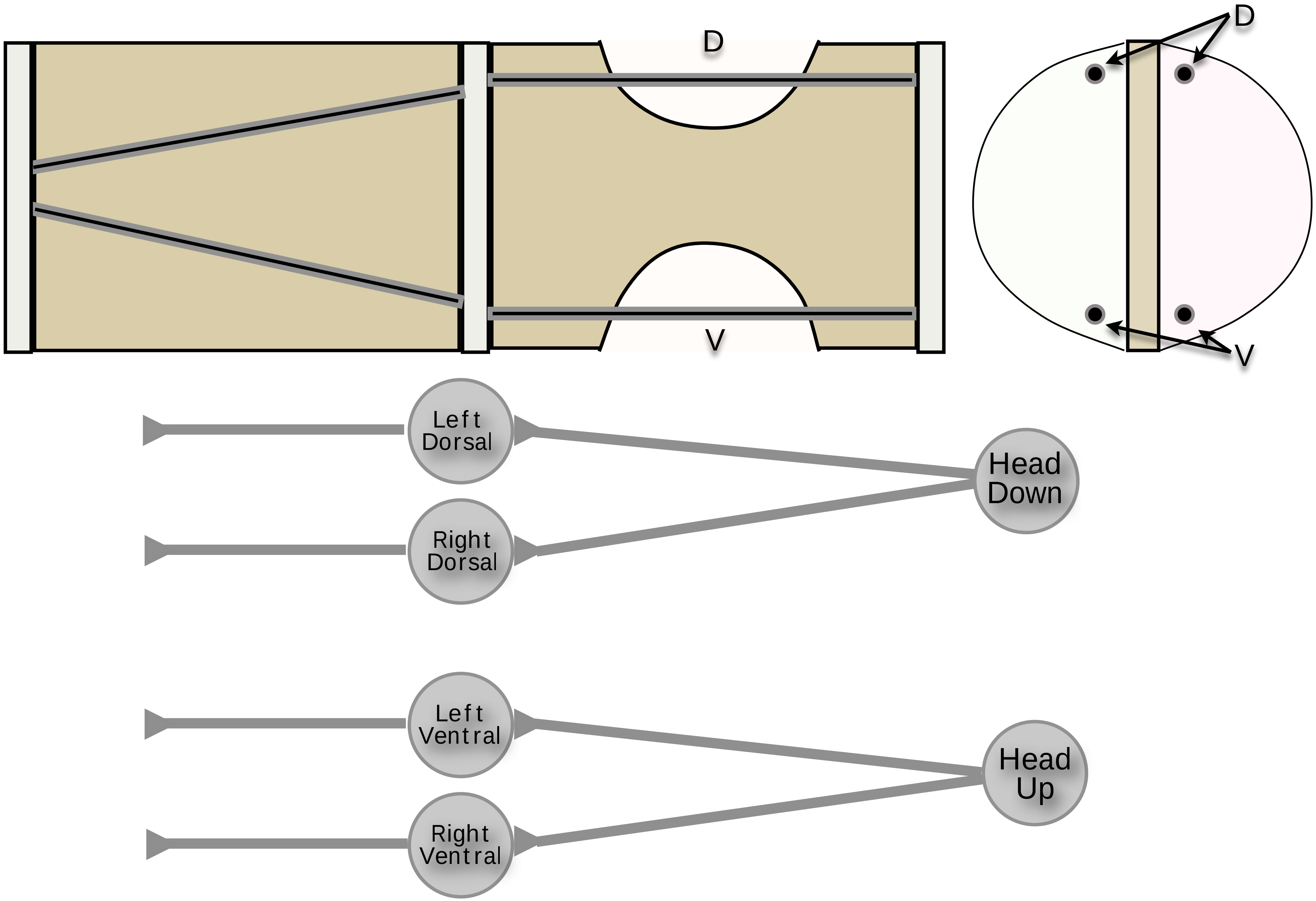
Figure 1.

Pitch | Roll

Head Down | Left Down

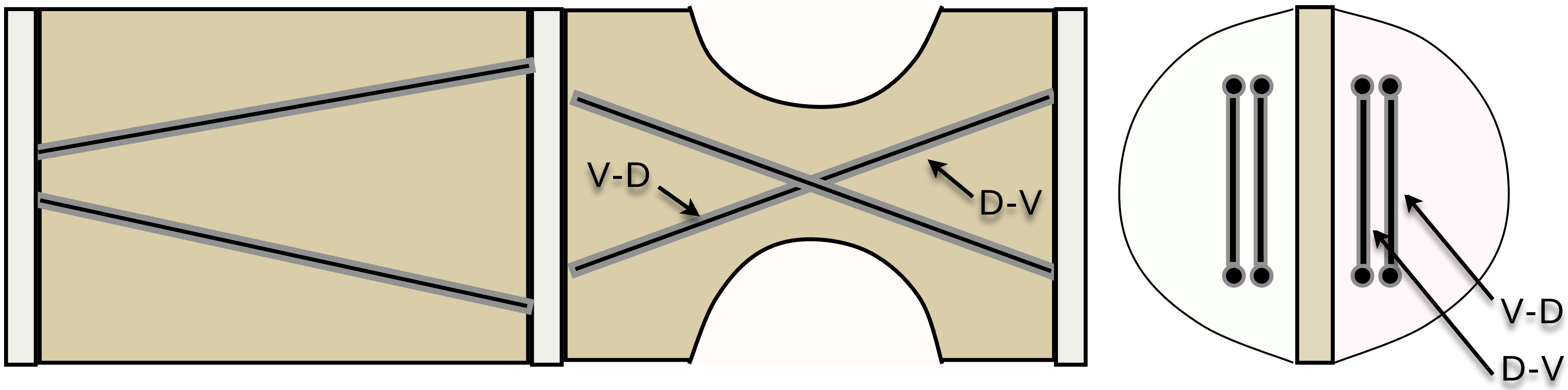
Head Up | Right Down

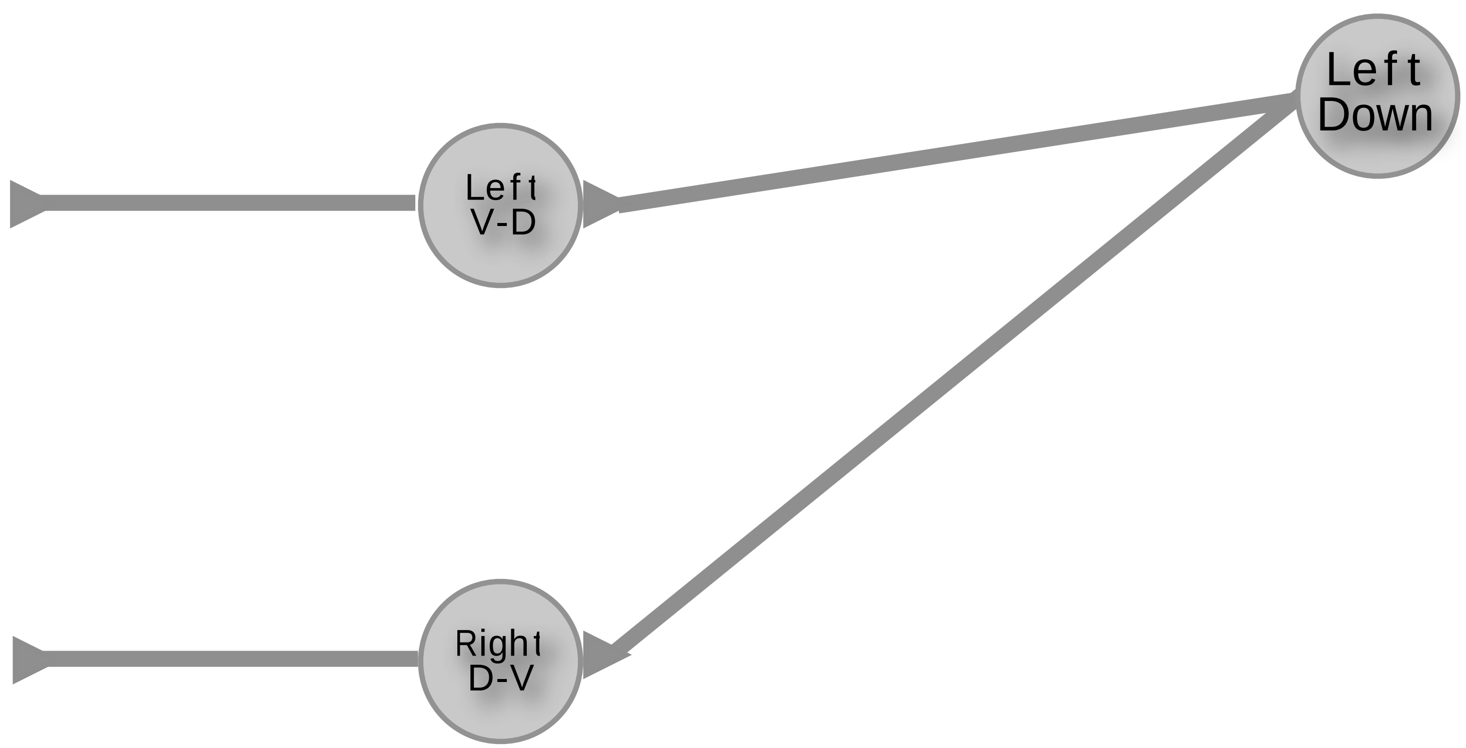
Pitch Layer



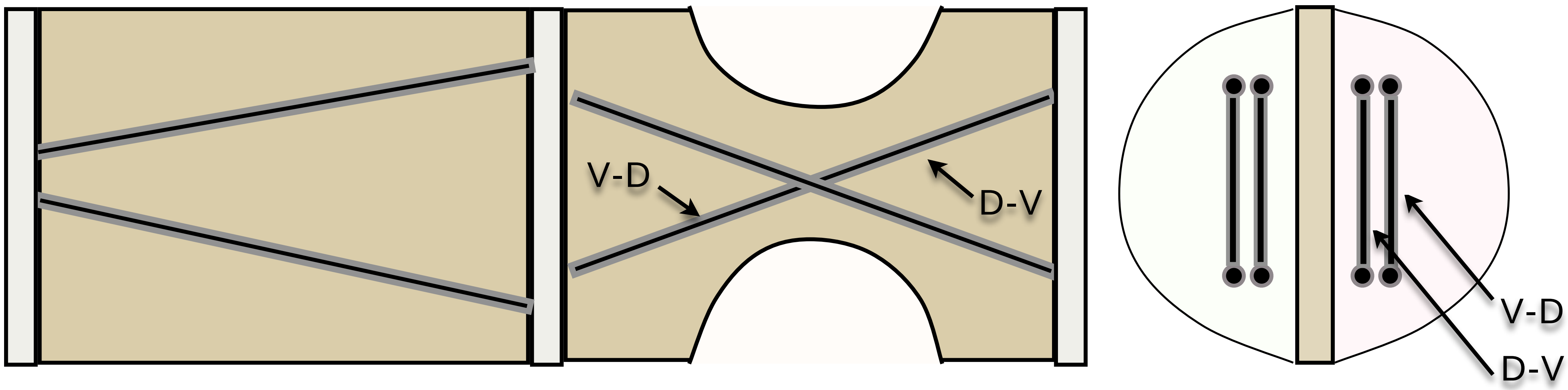
D
V
D
V
Left Dorsal
Right Dorsal
Head Down
Left Ventral
Right Ventral
Head Up

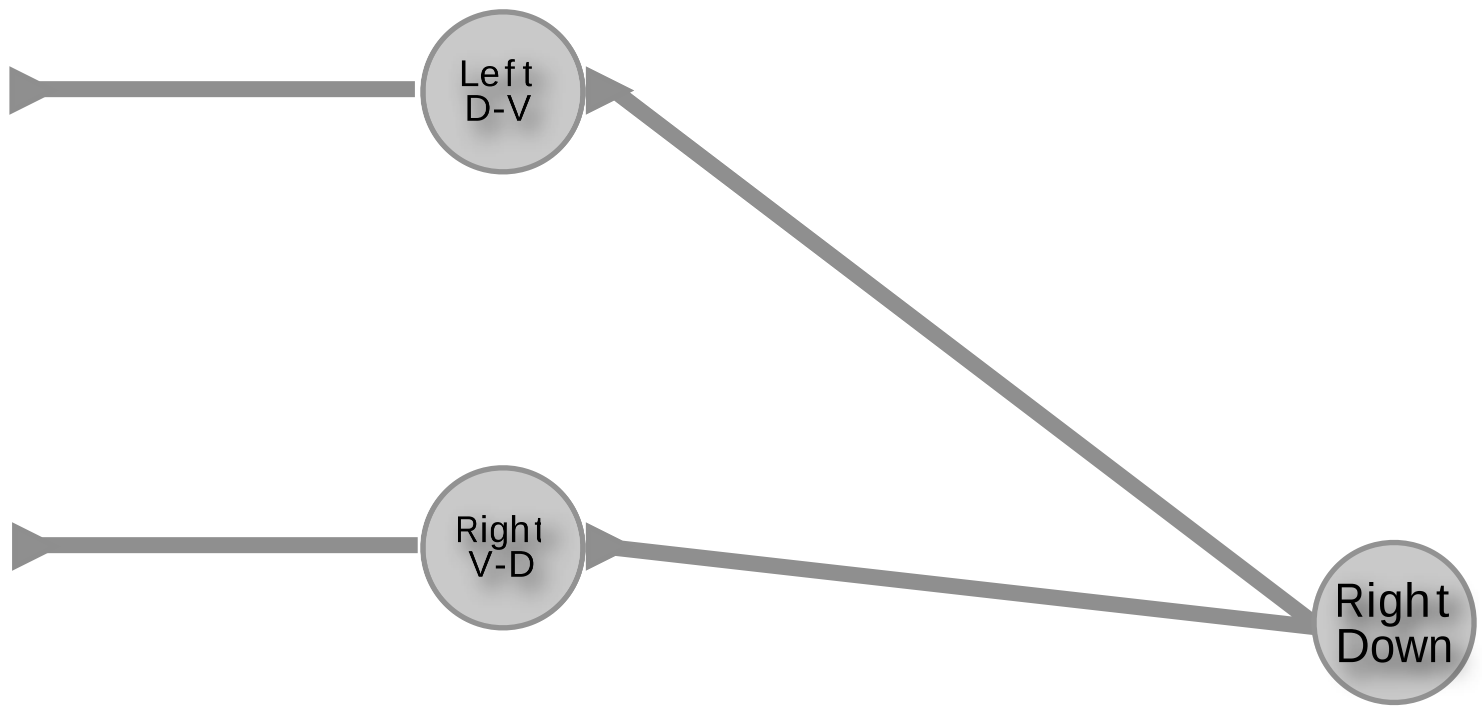
Roll Layer



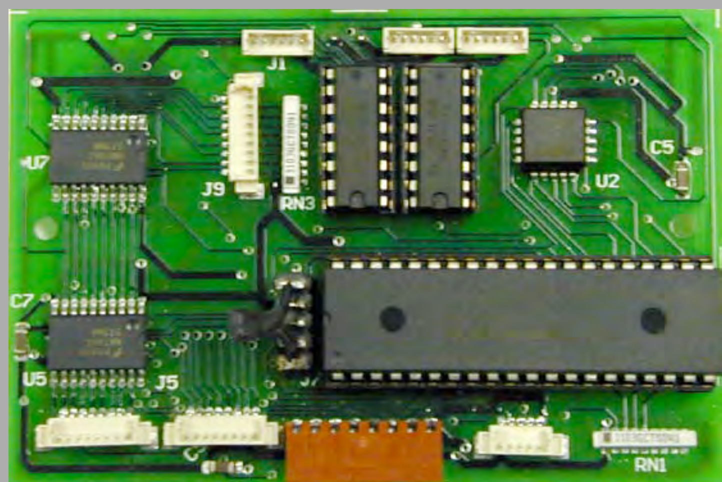


Roll Layer



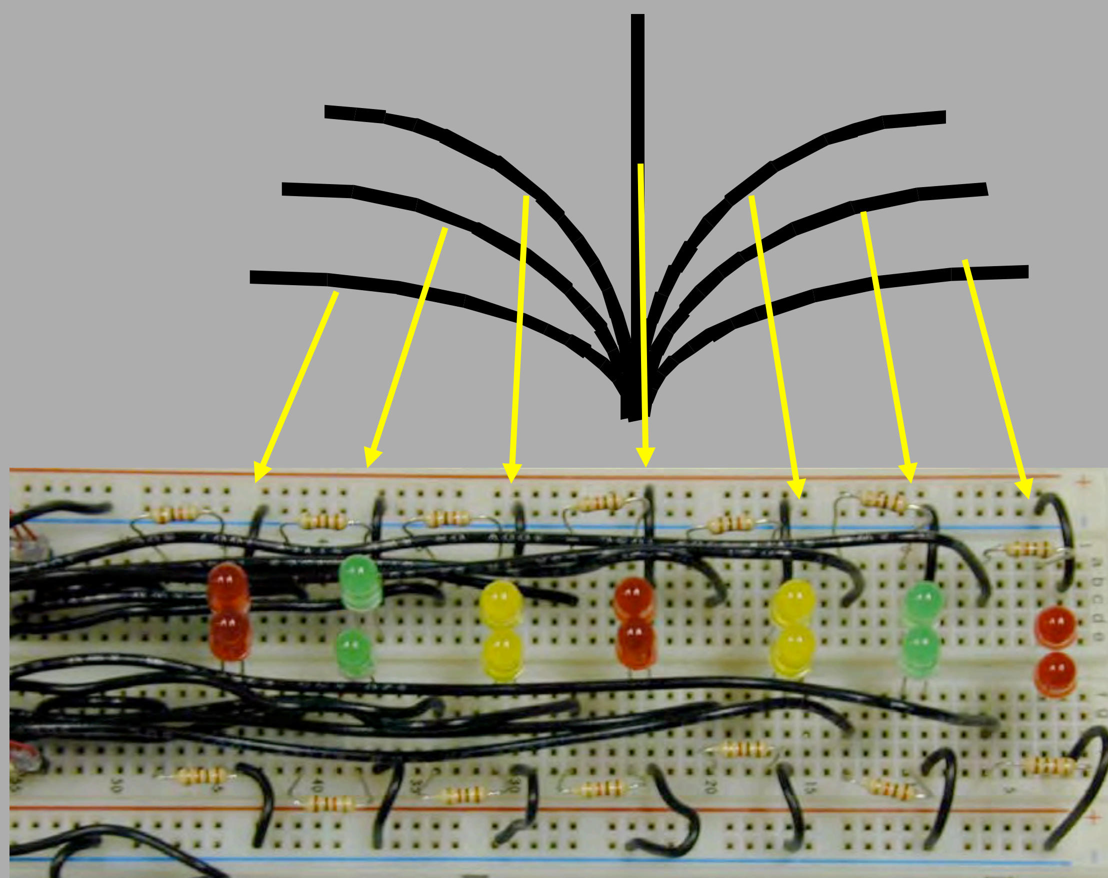


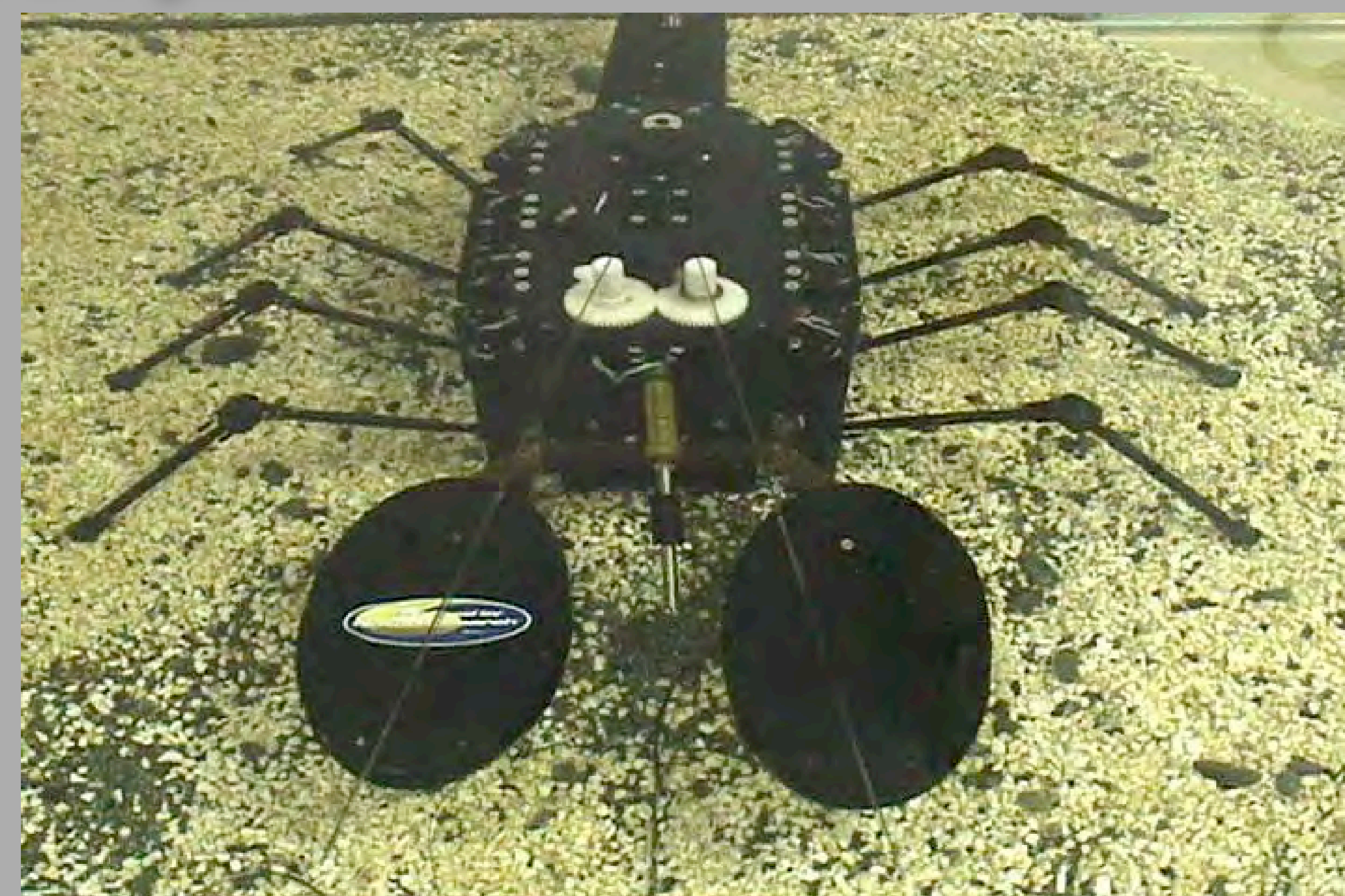
Strain Gauge Antenna



A/D Converter

- Discretizes Bridge output to 1 of 7 levels
- Indicates 3 degrees of bending to left or right

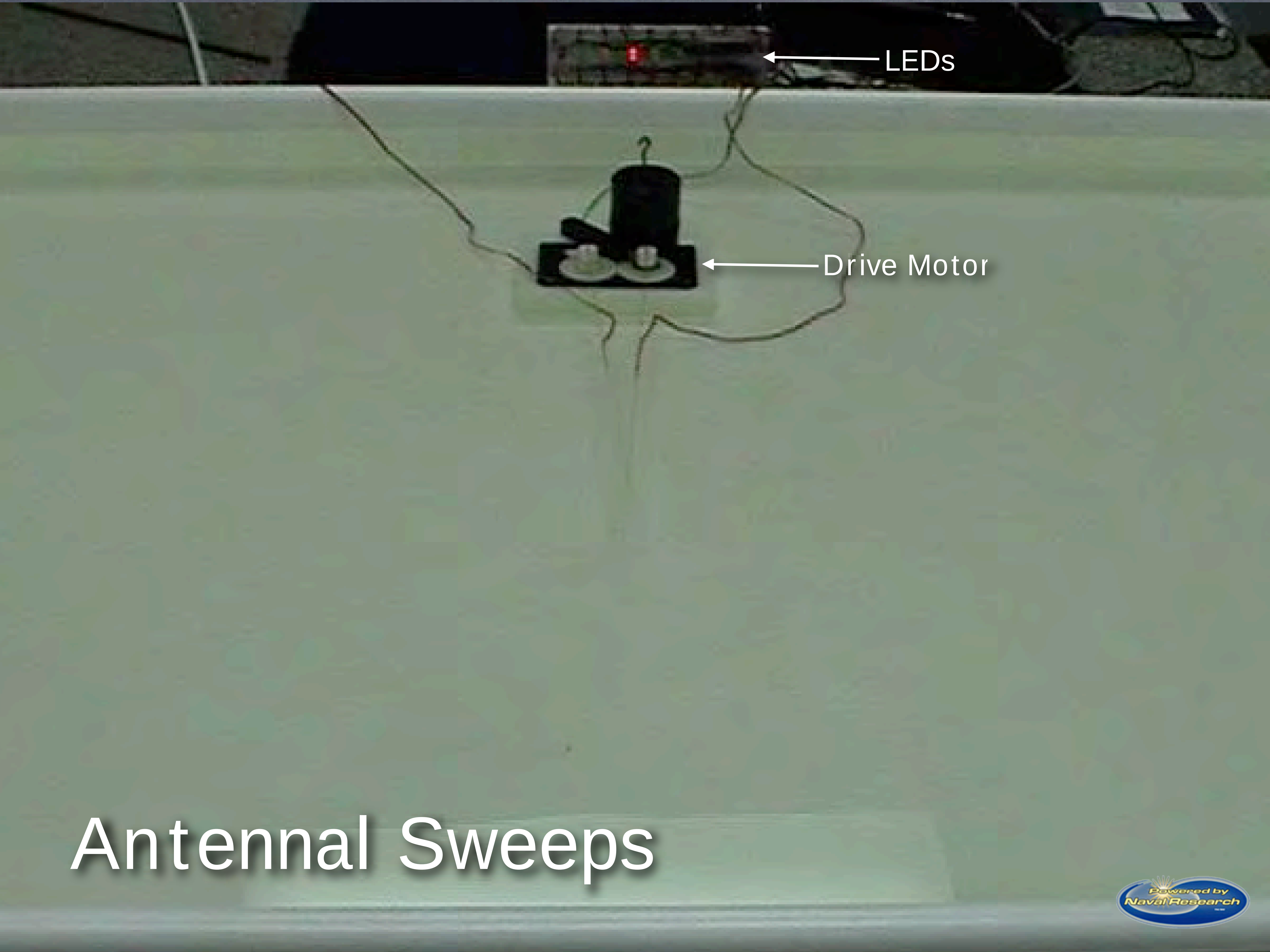


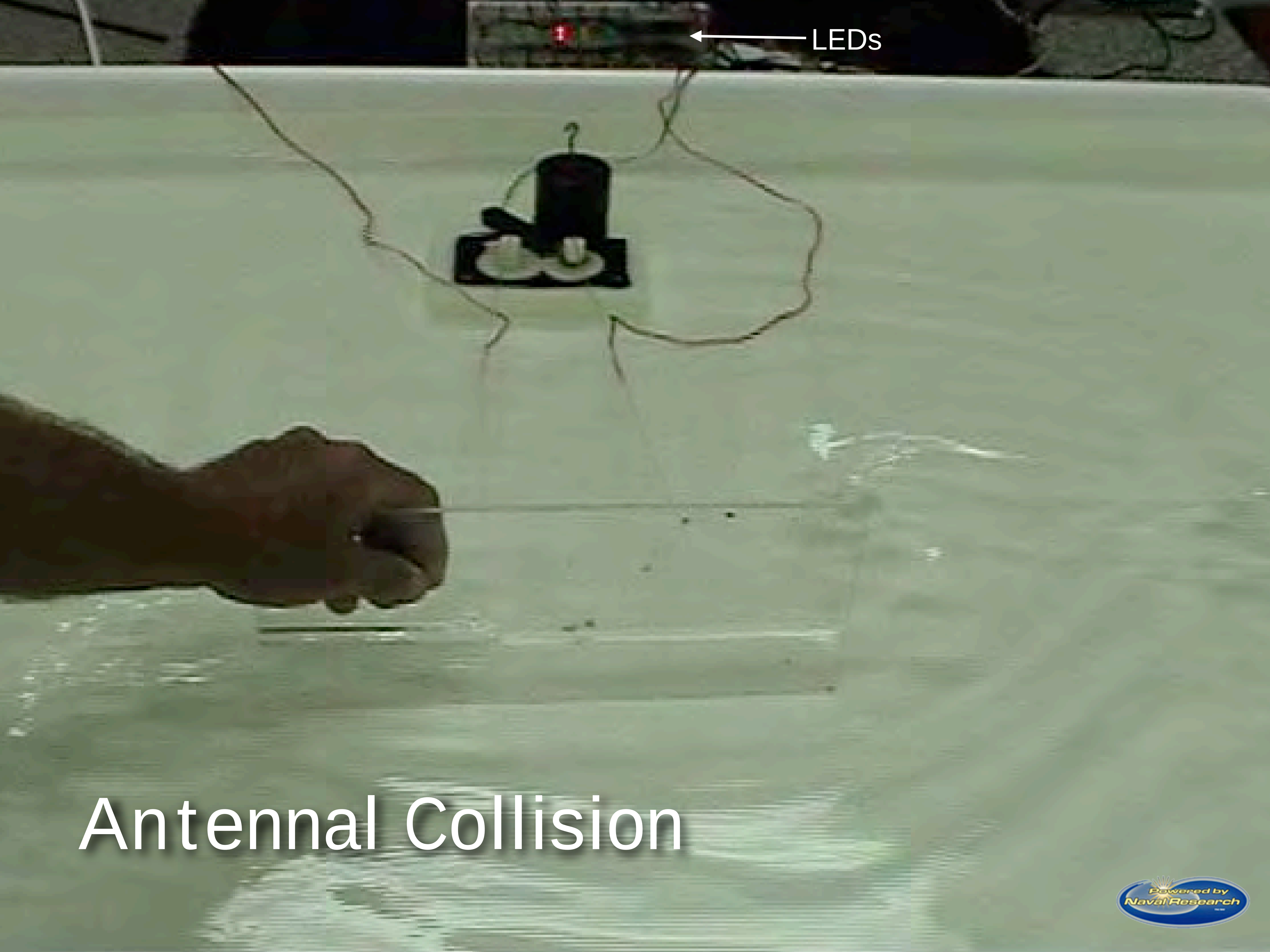


Motor Controller

Moves Antennae to 1 of 4 positions

DARPA Northeastern UNIVERSITY OFFICE OF NAVAL RESEARCH ONR


LEDs
Drive Motor
Antennal Sweeps
Powered by
Naval Research


LEDs
Antennal Collision
Powered by
Naval Research

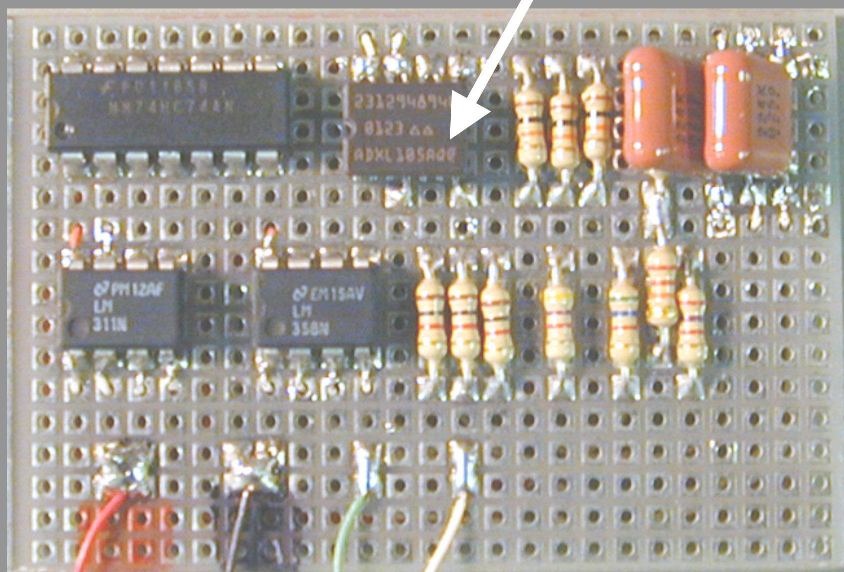
Lobster Cam

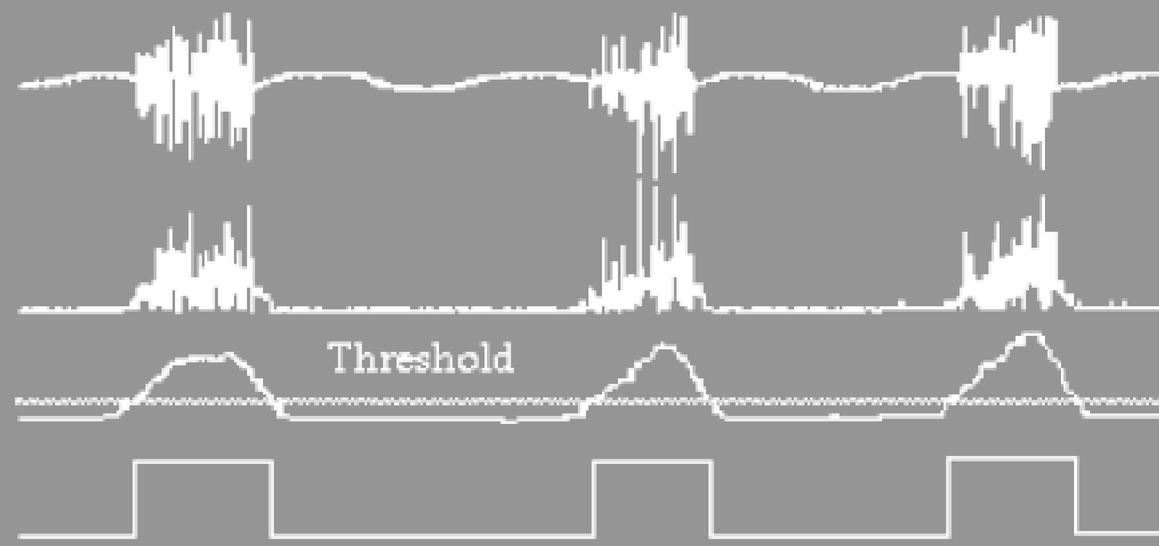
Bump Sense

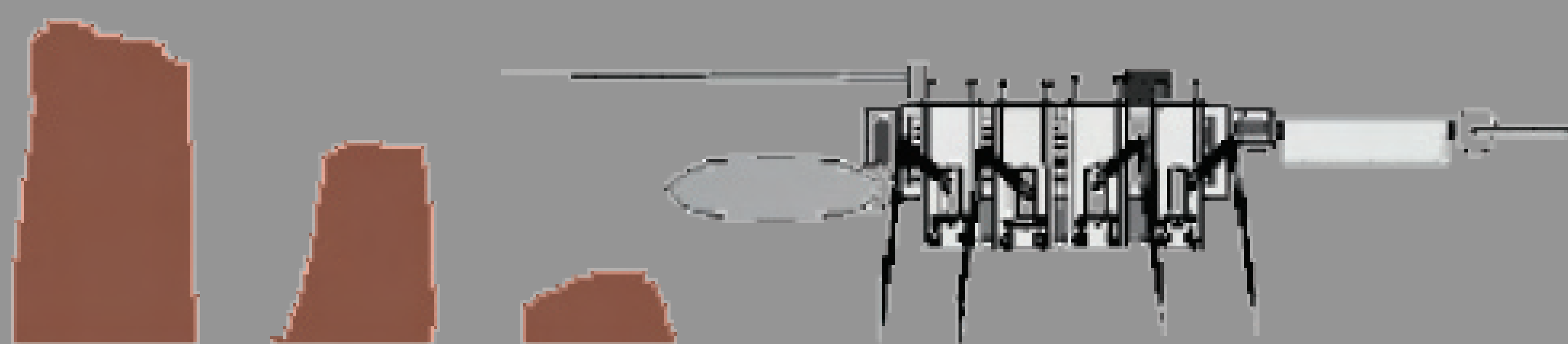
- Analyisis of collisions in blinded lobsters reveals that they mediate avoidance by detecting bumps with their chelipeds.
- This implies that bumps are a behavioral releaser of avoidance

Bump Sensor

Analog accellerometer







Walk Over

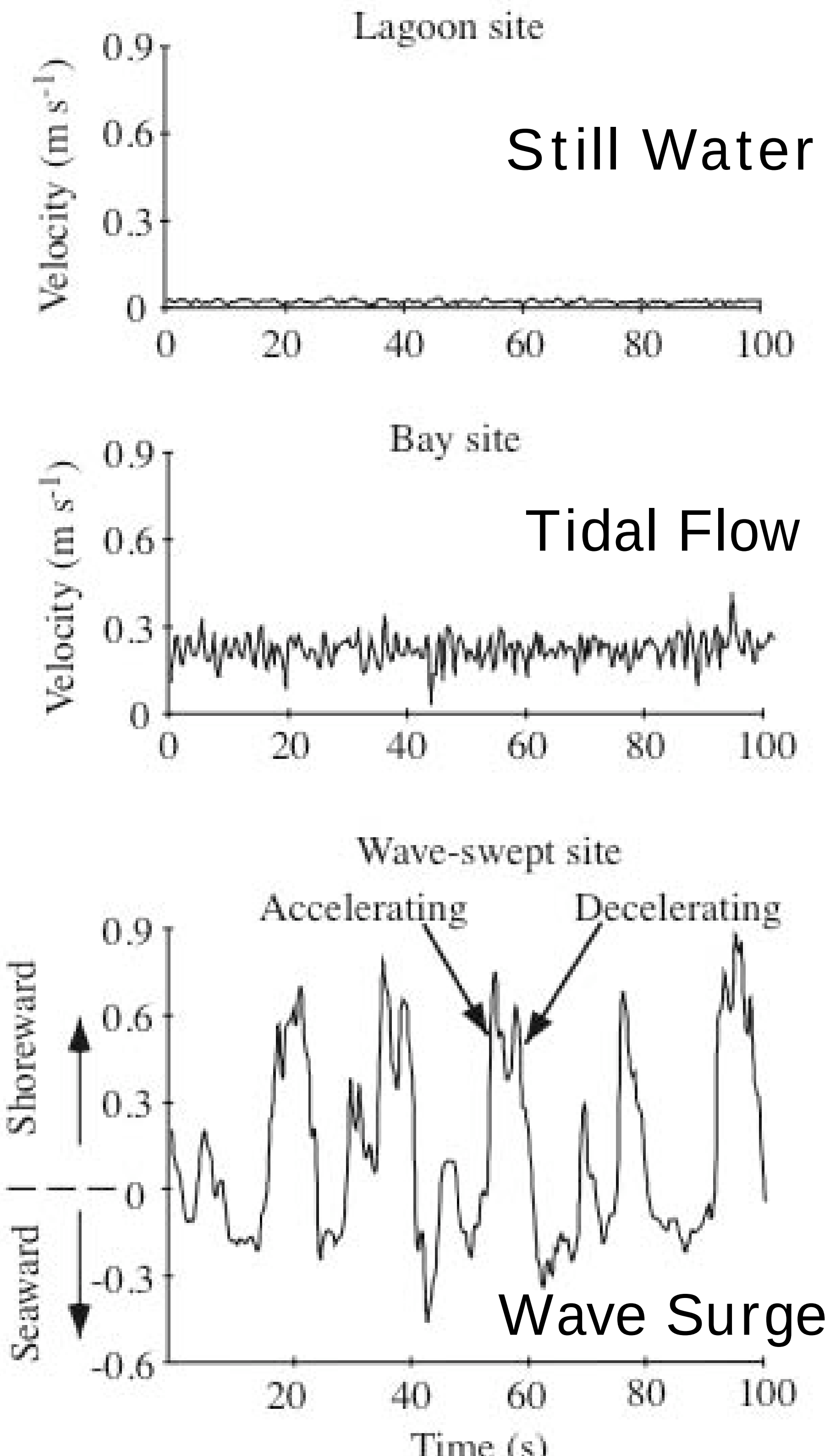
Climb Over

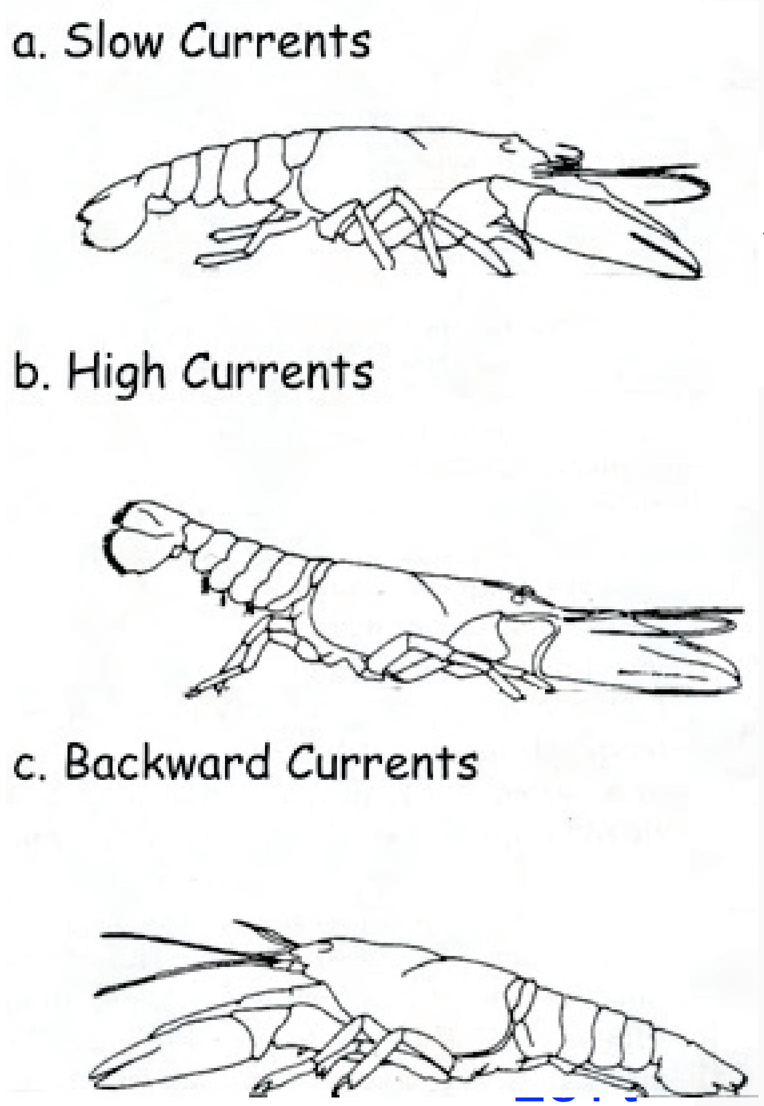
Circumnavigate

Northeastern University

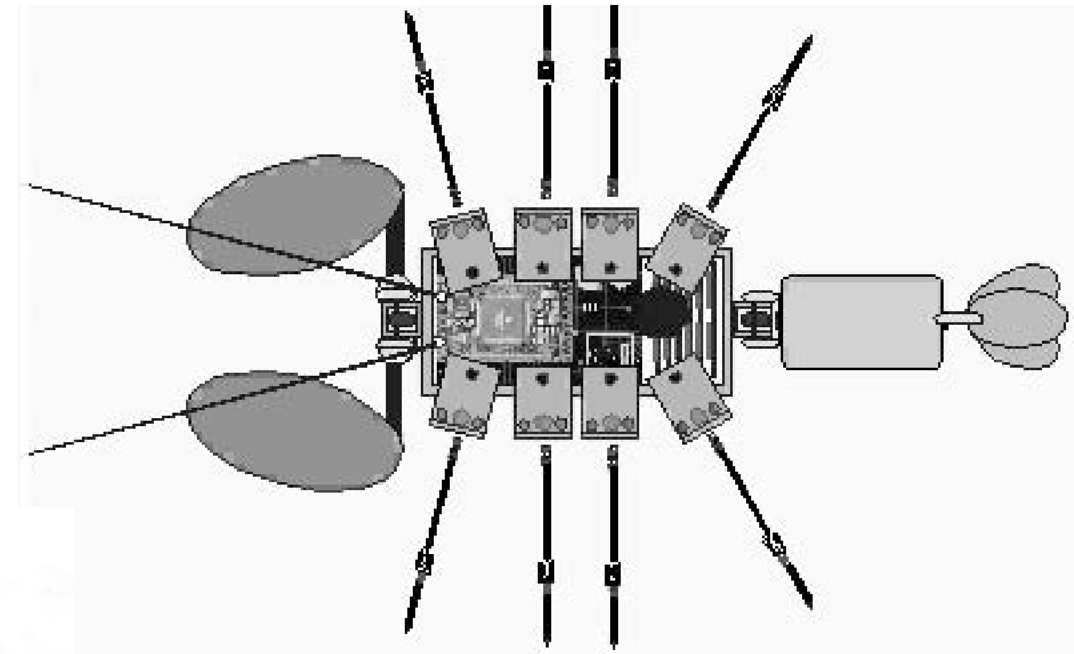
Powered by Naval Research

Rheotaxis

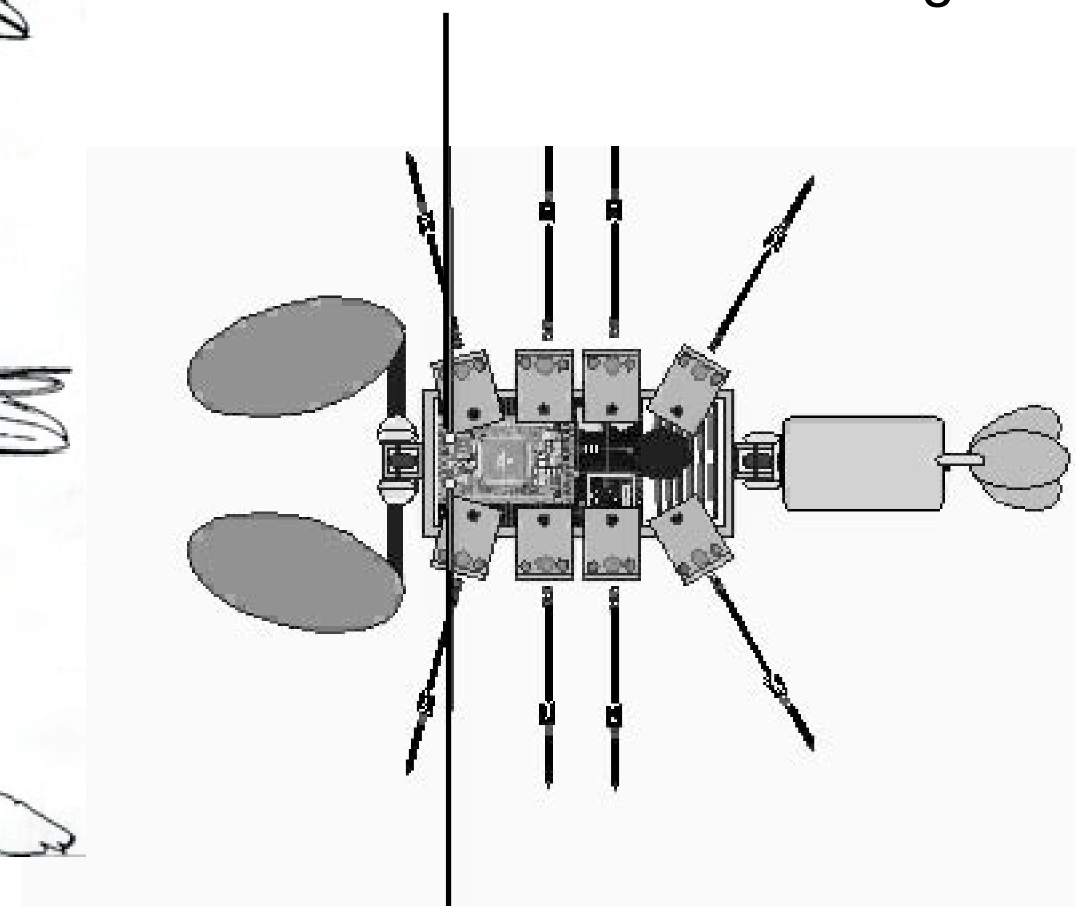


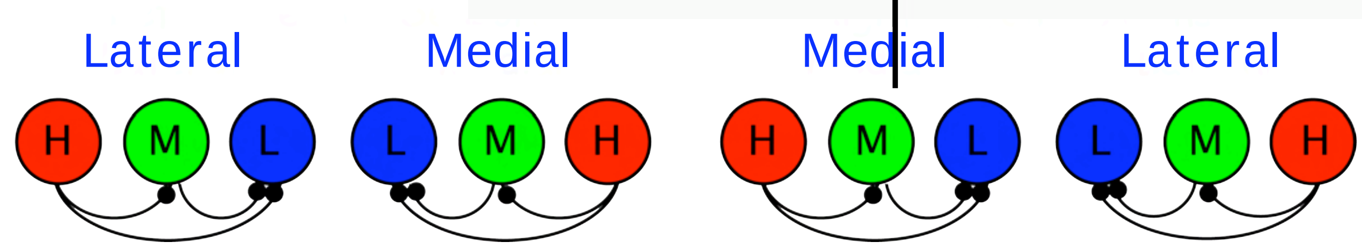


Antennae Forward: Lateral Surge



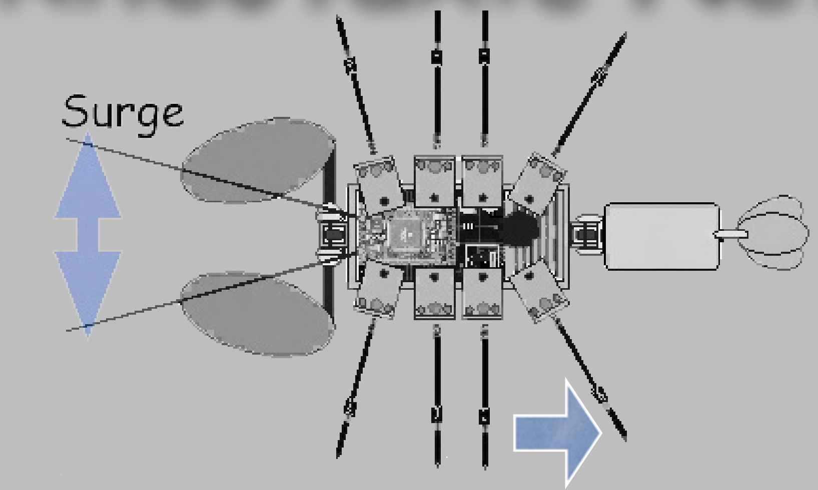
Antennae Lateral: Axial Surge

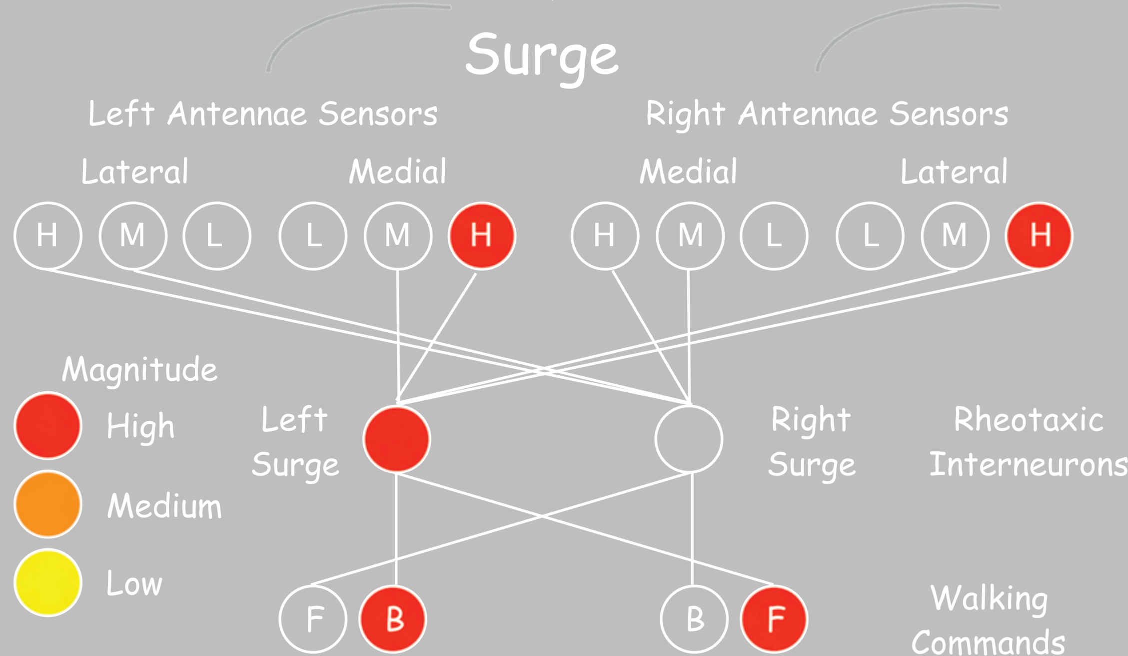


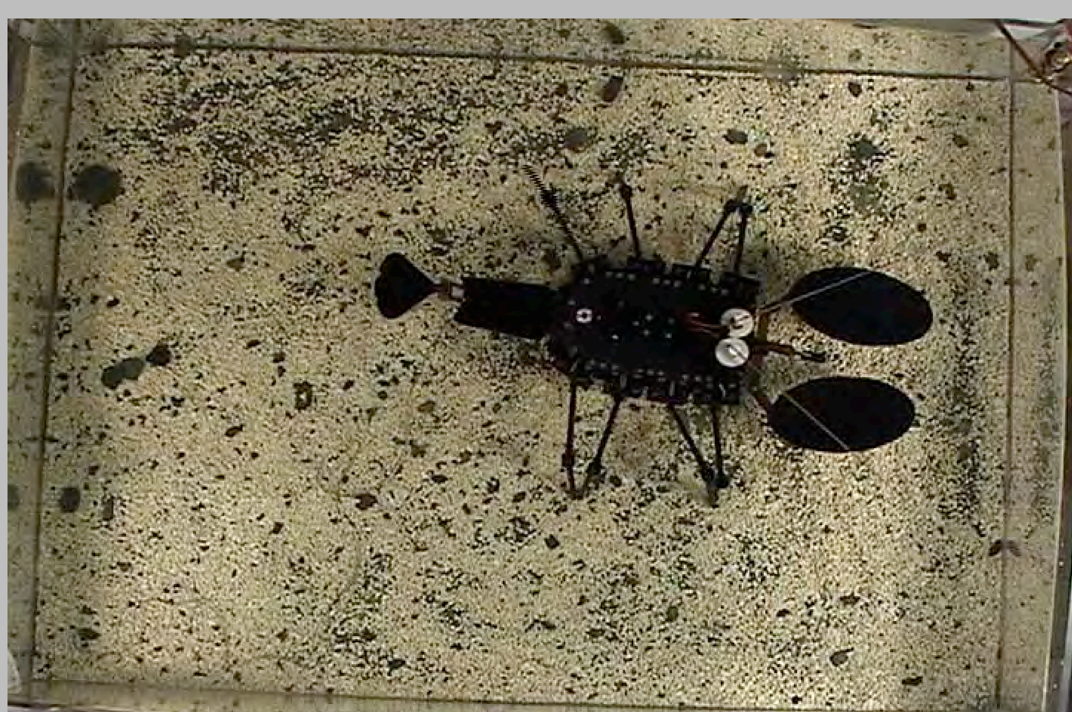


Marlene Martinez

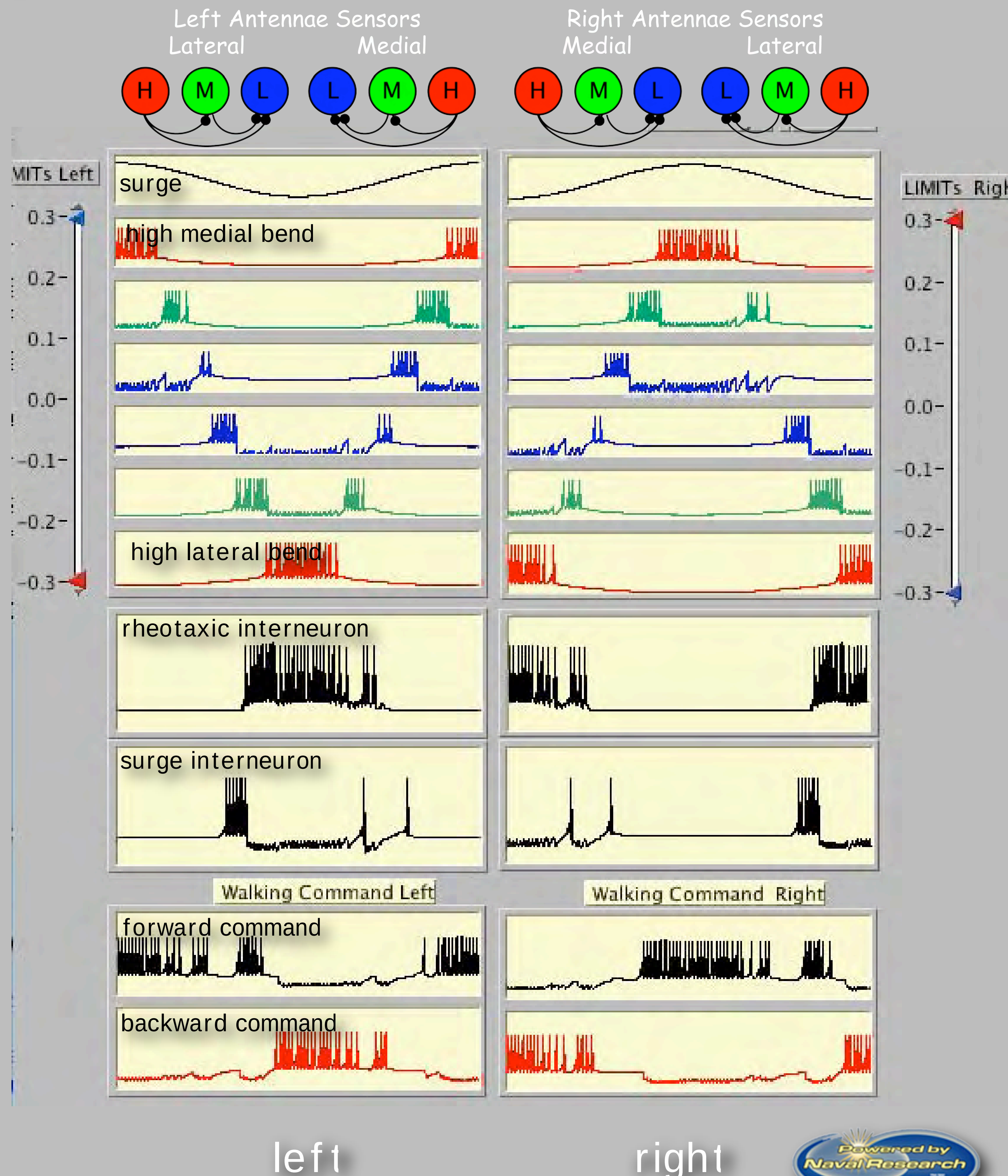
Rheotaxic Networks



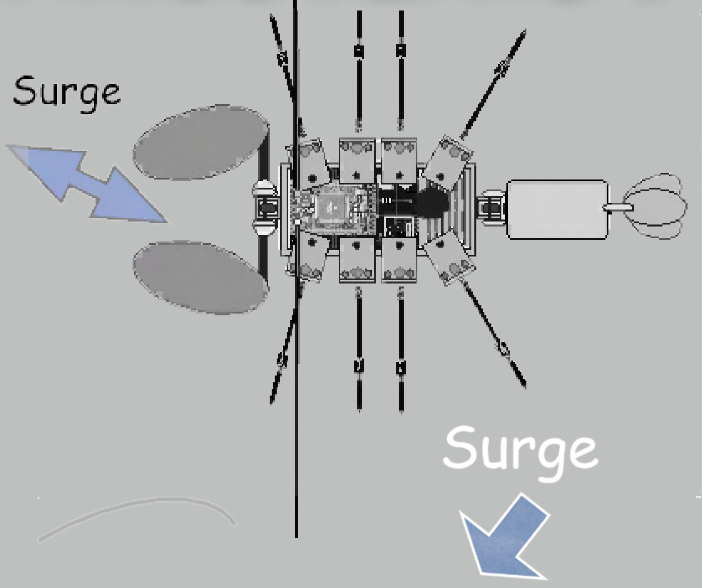


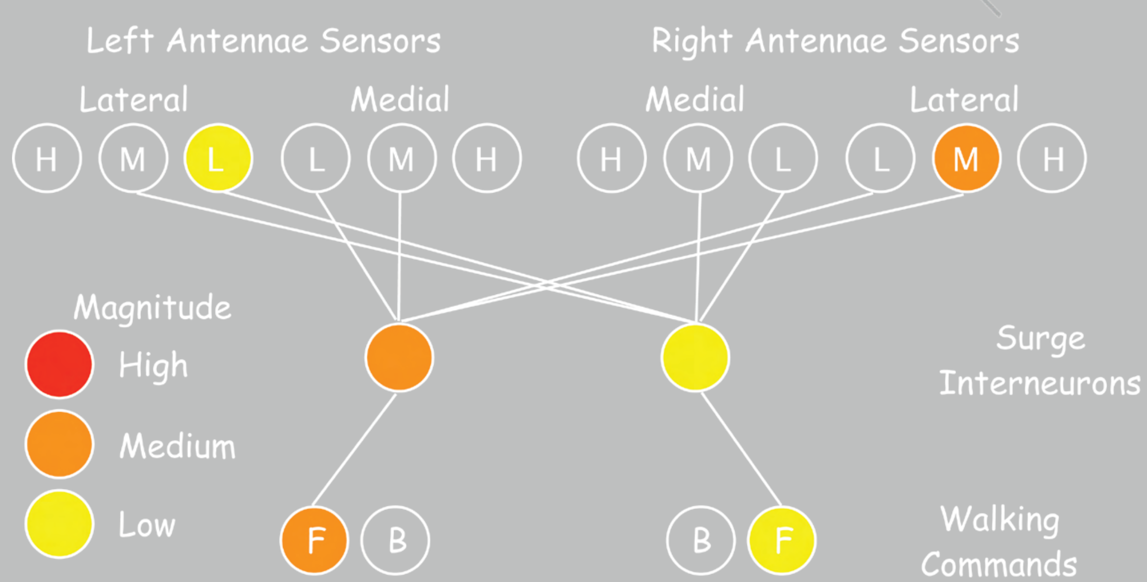


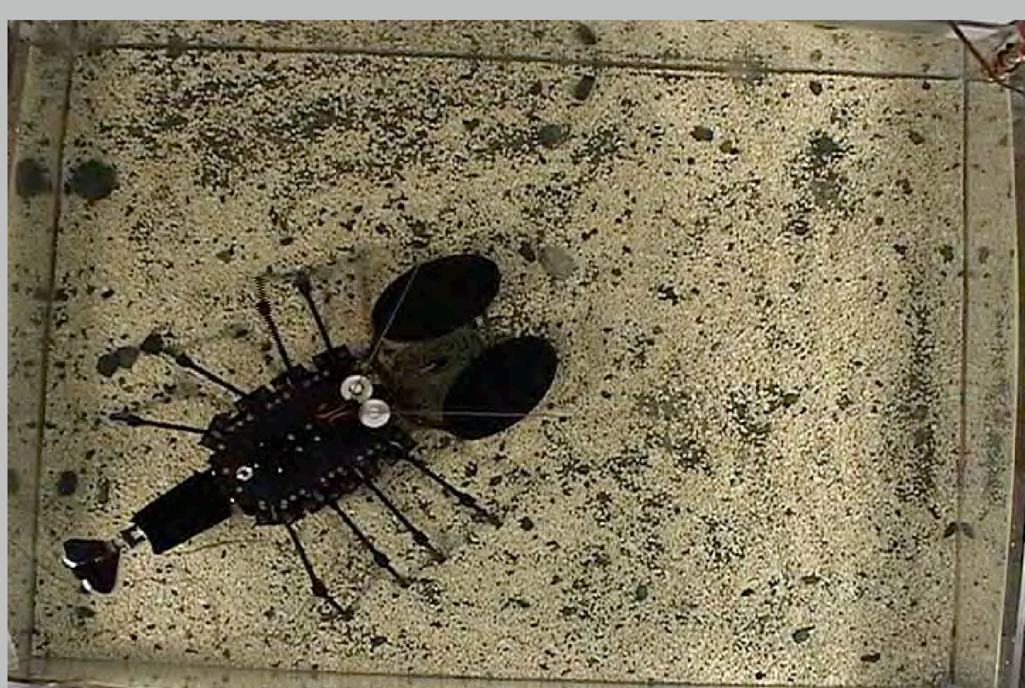
Rotational



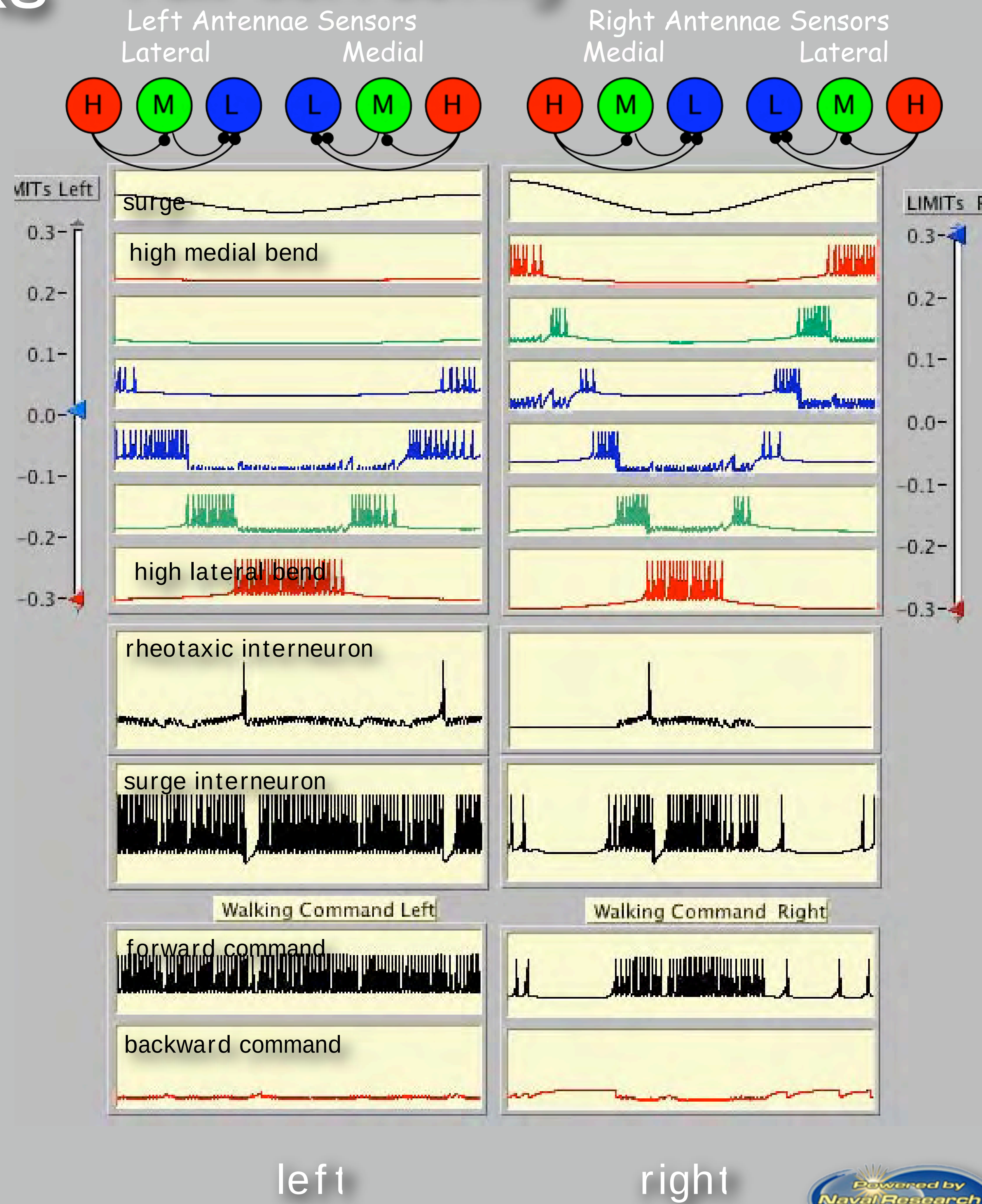
Rheotaxic Networks





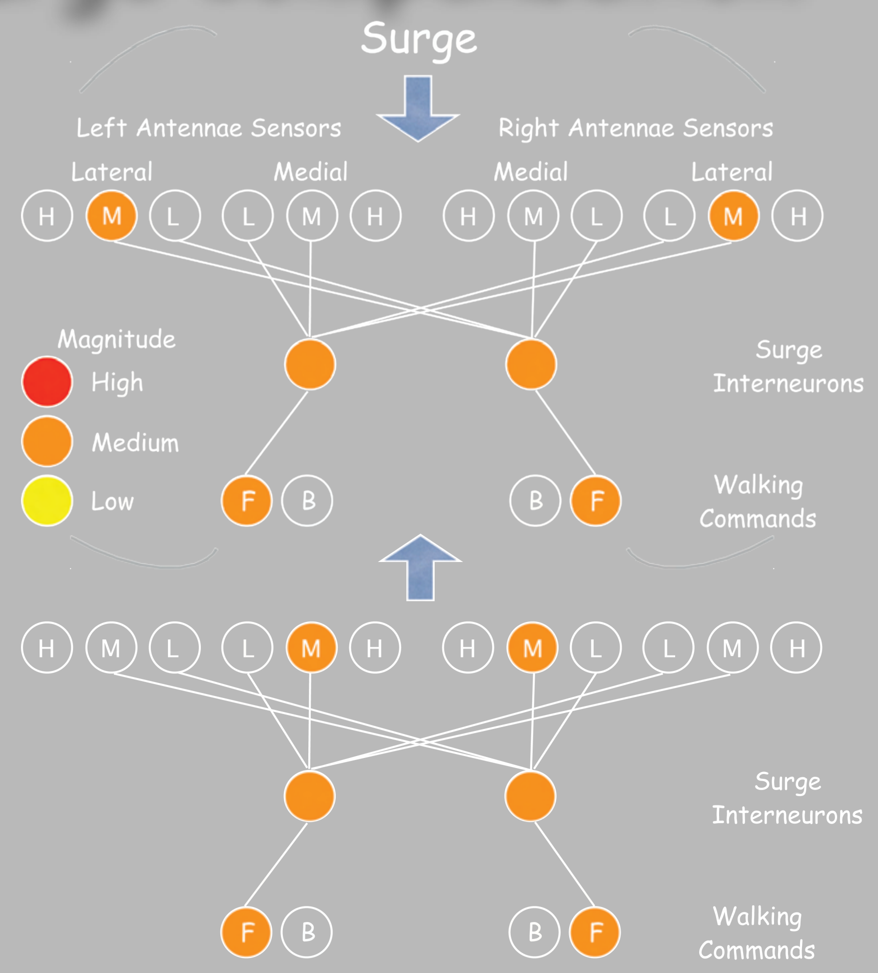


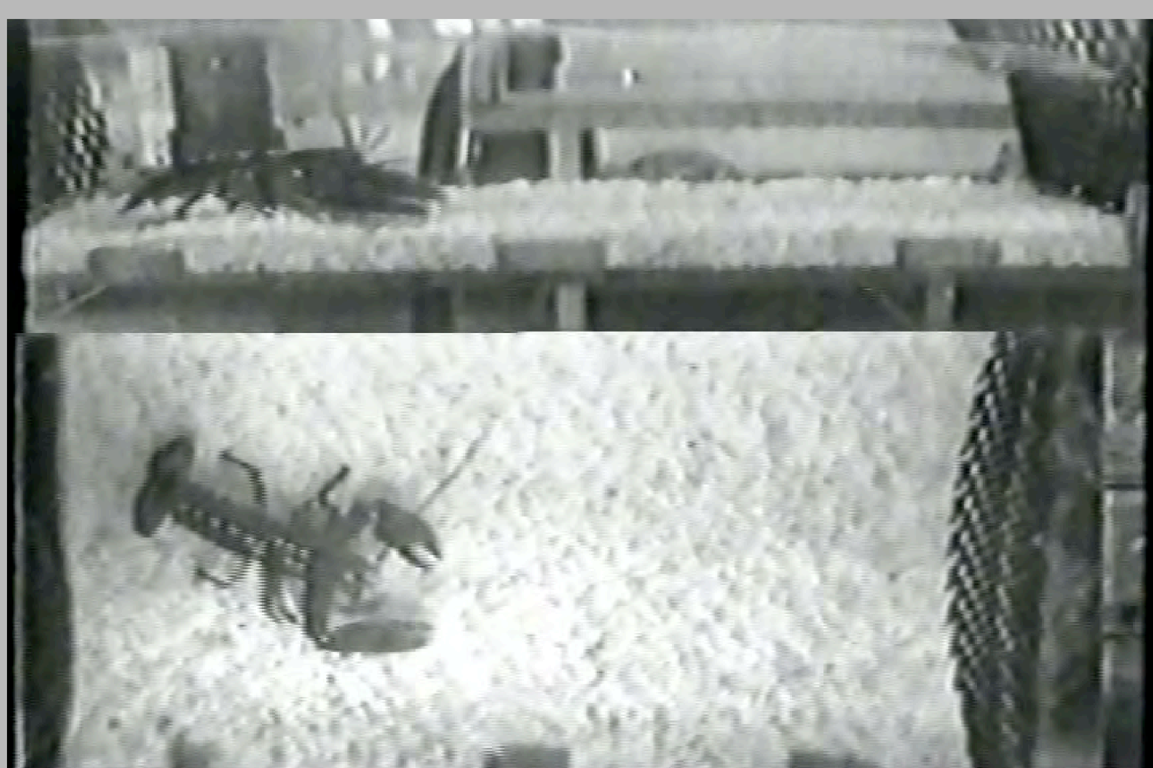
Yaw Correcting

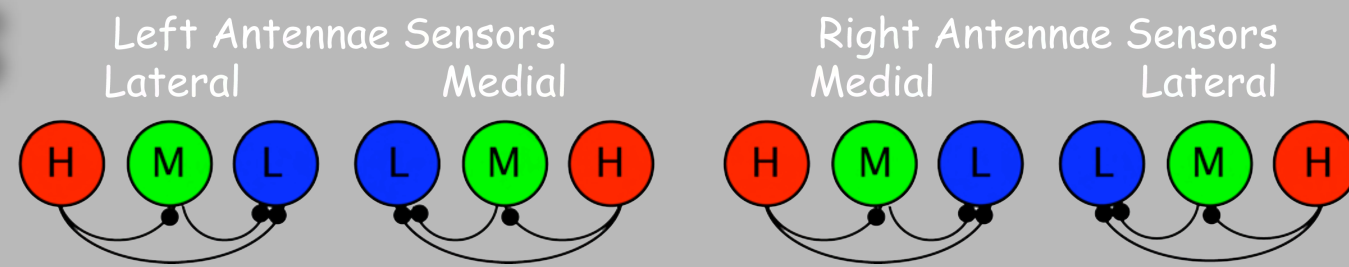


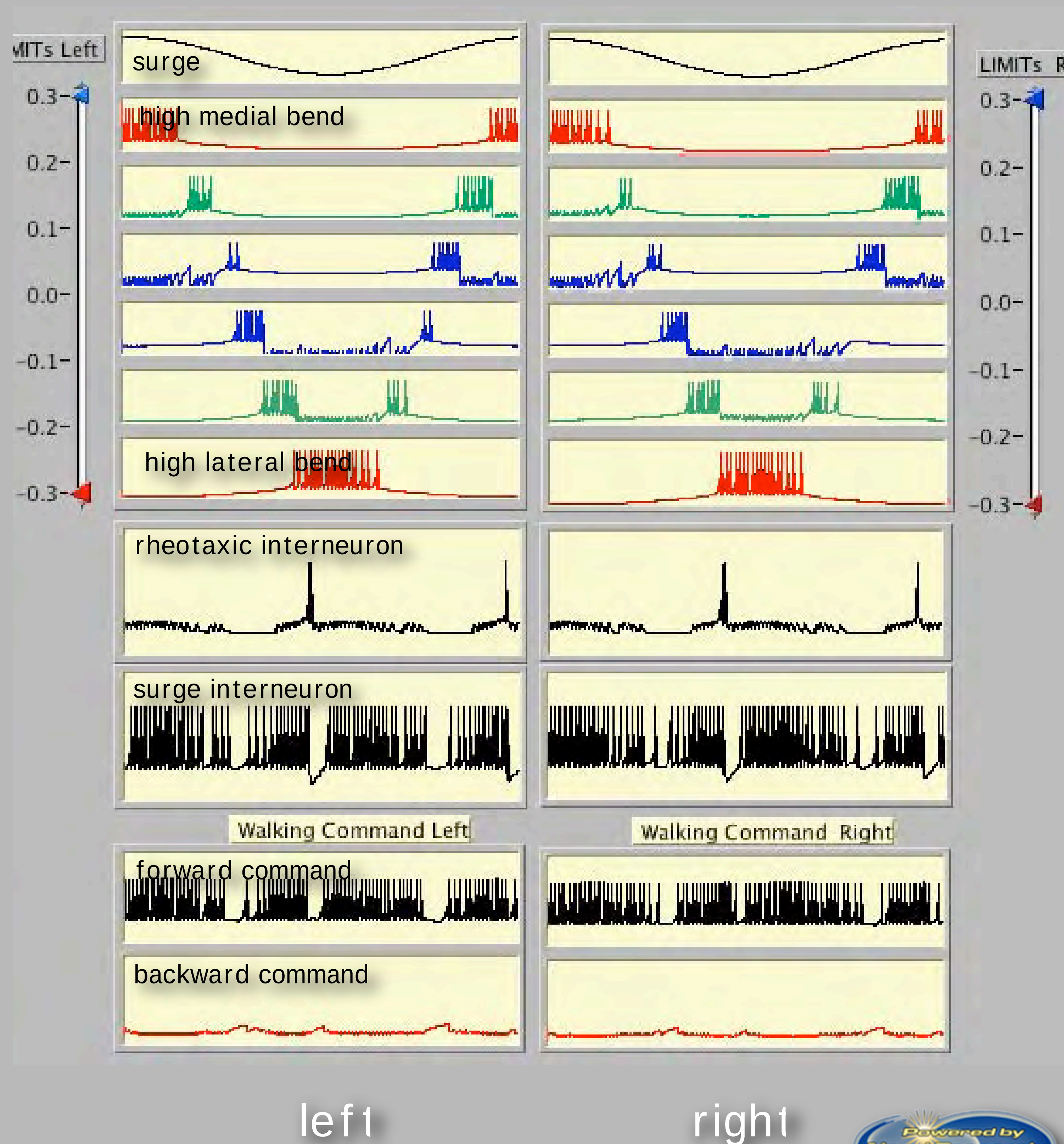
Rheotaxic Networks

Surge Compensation

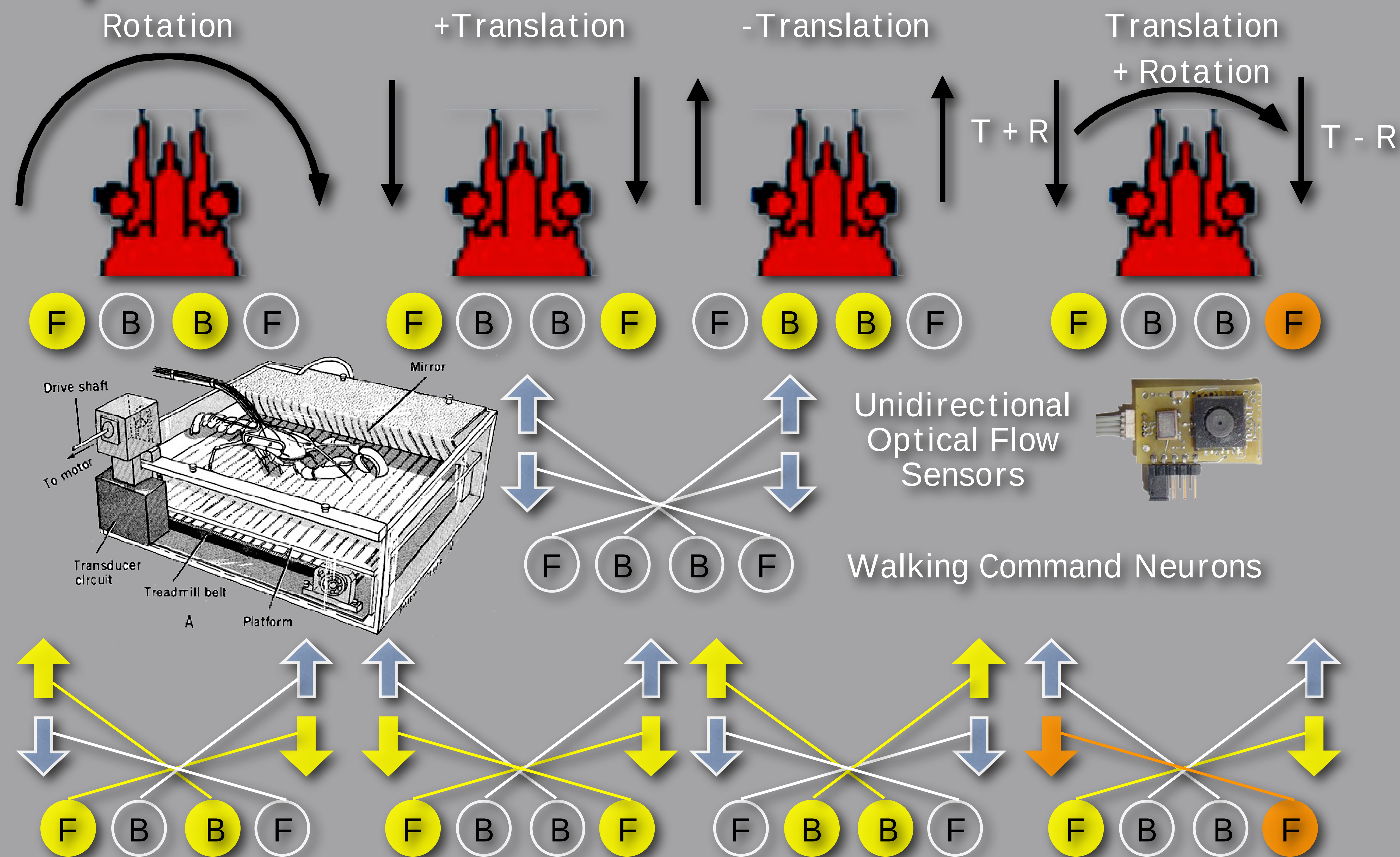




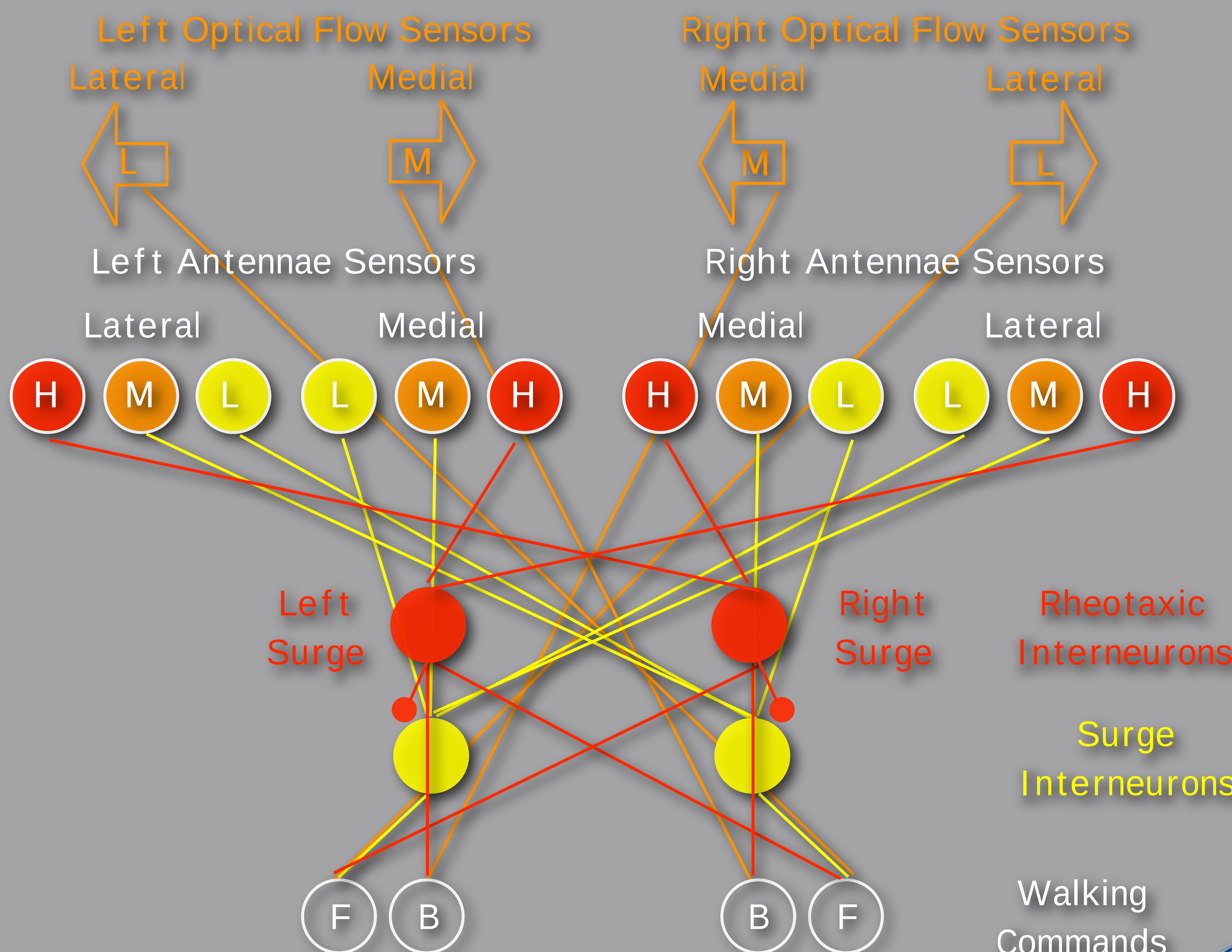




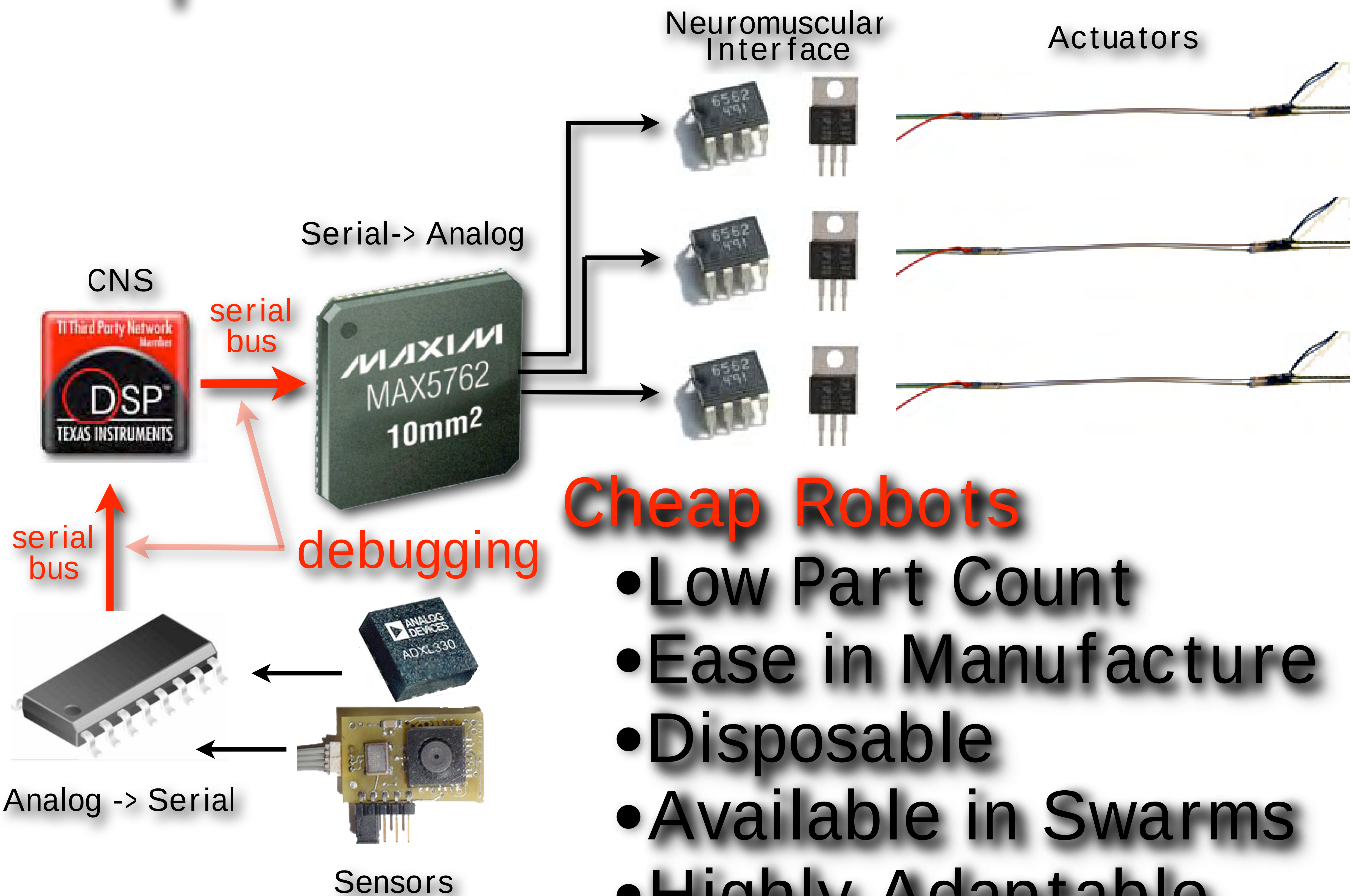
Optical Flow Reflexes



Sensor Fusion



Simple Electronics



Cheap Robots

- Low Part Count
- Ease in Manufacture
- Disposable
- Available in Swarms
- Highly Adaptable

Collaborators

Sponsors

Alan Rudolph: DSO

Tom Wagner: IPTO

Joel Davis

Northeastern University

Mobile Robotics for In vivo Surgical and Battlefield Applications

Mark Rentschler

Postdoctoral Research Associate

University of Nebraska

Dmitry Oleynikov – *Department of Surgery*

Shane Farritor – *Department of Mechanical Engineering*

In vivo Robotics for Surgery

- Laparoscopy
  - Minimally invasive surgery (MIS)
  - Small ports (5-20mm)
  - Insufflation

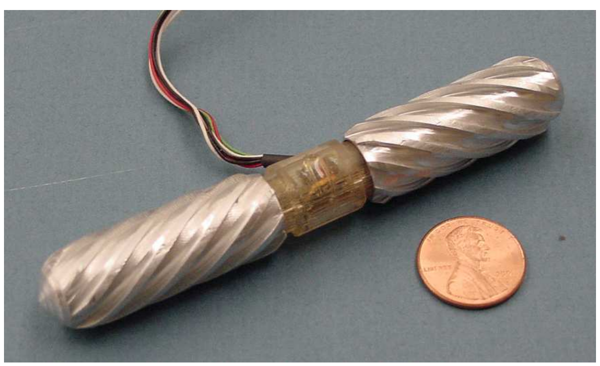
- MIS challenges
  - Entry port constraint
  - Reduced dexterity
  - Limited perception

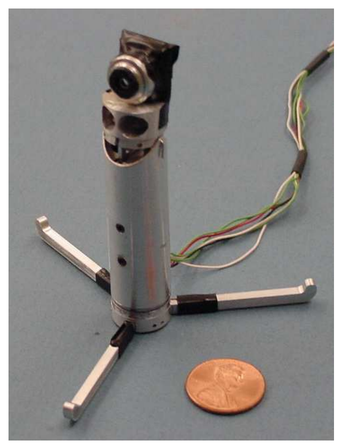
da Vinci Surgical Robot

- Scaled motion, reduced tremor
- Large, expensive
- Entry port constraint

Abdominal *In vivo* Robots

- Not constrained (wireless)
- Enhanced field of view (multiple angles)
- Clamp, cut, cauterize, coagulate
- Small, cheap, deployable





Pan and tilt in vivo test

In vivo Robotics for Battlefields

- ~90% of battlefield deaths take place within 30 minutes of the initial injury
- ~ 50% of these deaths are due to hemorrhaging in the chest and abdomen
- Immediate surgical treatment is often required, but difficult

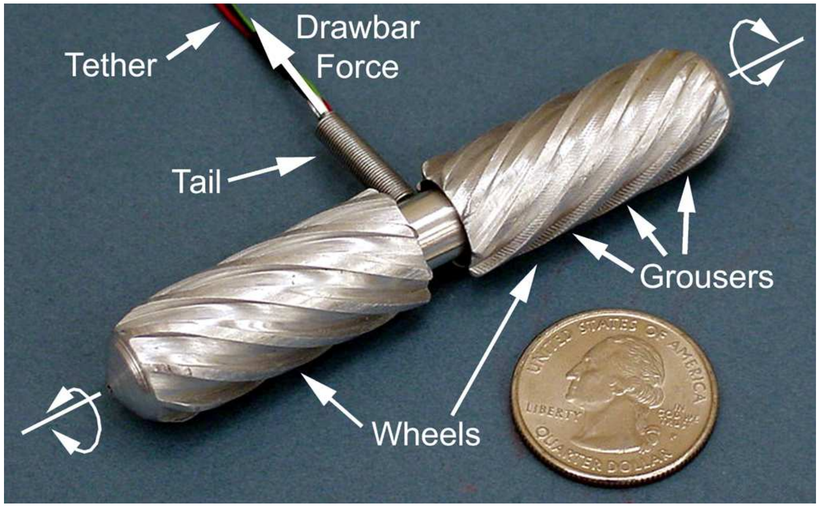
Need the surgeon to be a "remote first responder"

Miniature In Vivo Robots

Tele-surgery & tele-mentoring

Mobile Robot Platform

- 2 independent wheels
  - 2 electric motors
  - Forward, reverse, turning
  - Tail to prevent spinning
- 12-15mm diameter
- Tethered for power, or wireless
- Camera
- Biopsy
- Sensors



In Vivo Mobility Challenges

- *In vivo* environment:
  - Deformable
  - Slick
  - Hilly

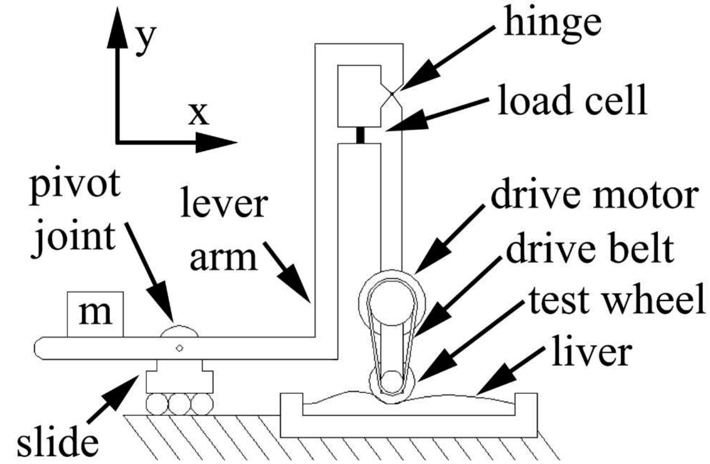
- Too little traction
- Too much traction
- High centering

- Modeling
- Wheel testing

Mobility Challenges

Experimental Platform

- Linear slide
- Induce slip
- Adjust normal force
- Measure drawbar force



$$SR = 1 - \frac{\dot{x}_{cm}}{r\dot{\theta}_{cm}}$$

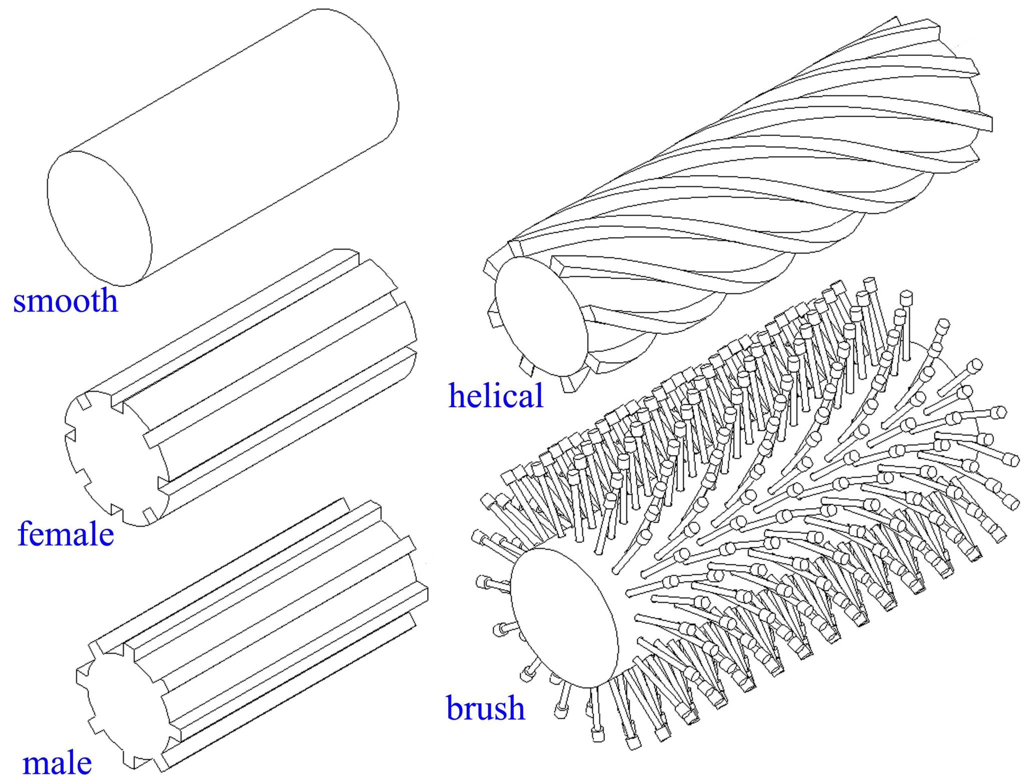
- Test complex geometries

Experimental Platform

Wheel Profiles

Profiles Tested

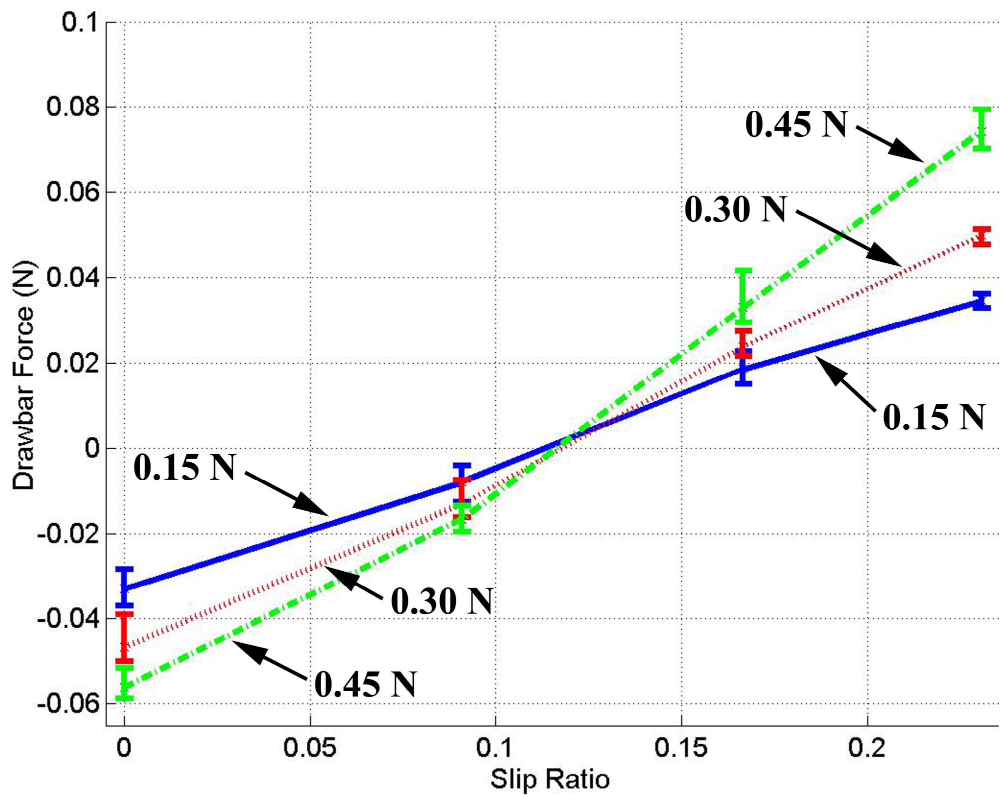
- Smooth
- Female
- Male
- Helical
- Brush



Experimental Results

Helical wheel design

$$SR = 1 - \frac{\dot{x}_{cm}}{r\dot{\theta}_{cm}}$$

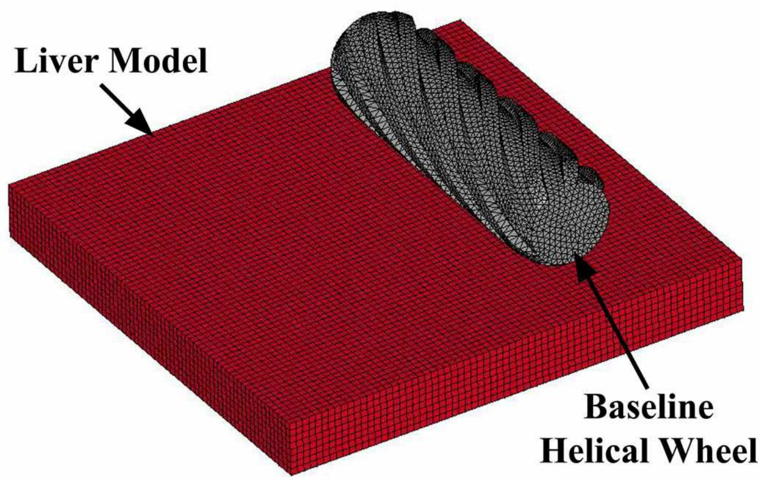


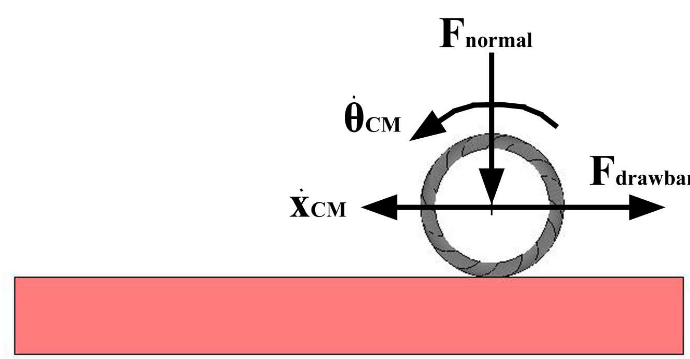
Wheel Test Results

- Reduce motion resistance
  - Larger diameter, less ground pressure
  - Less ground pressure, less sinkage, less torque loss
- Minimize fluid effects
  - Good tread design
  - Avoids hydroplaning
- Helical profile is superior

Finite Element Analysis

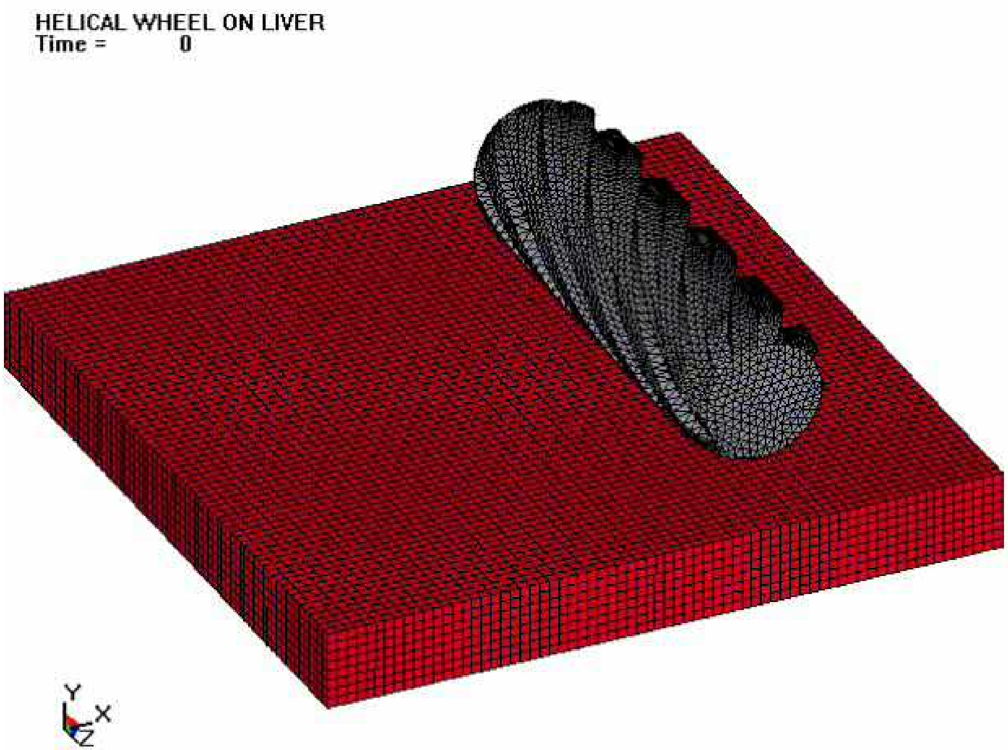
- Loads – vary the normal forces (weight)
- Motions – translation and rotation
- Results – force transducers measure drawbar force
- Wheel is rigid
- Tissue is liver material model (SLS model)





Tissue Damage

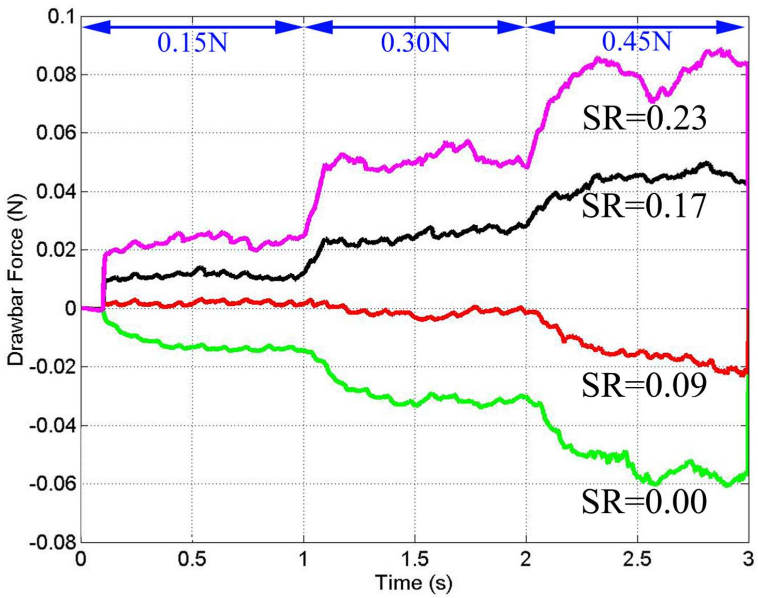
- Routine grasping forces of 40 N
  - Corresponds to pressures of ~ 400 kPa
- Finite element model shows max stresses of 1.95 kPa

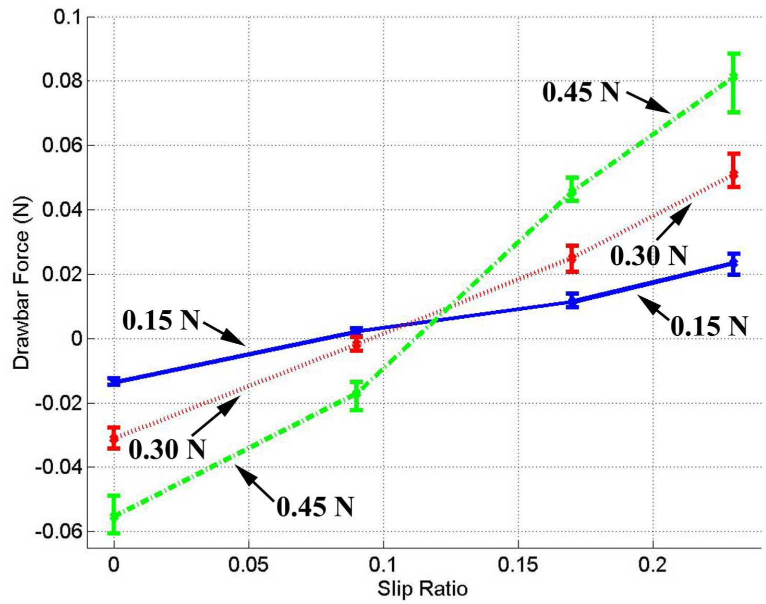


[Finite Element Modeling]

Drawbar Forces

- Four slip ratios, three weights
- Results compare favorably to lab data
  - Approximately same magnitudes
  - Same weight trend
  - Same slip ratio trend





Geometry Analysis

- Larger diameter is better
  - less motion resistance
- Lower pitch angle is better
  - high stress concentrations
  - 2 treads -> smooth velocity profile
- Thinner tread is better
  - higher stress concentrations
- Larger tread depth is better
  - Up to a point ~ 1.5 mm depth

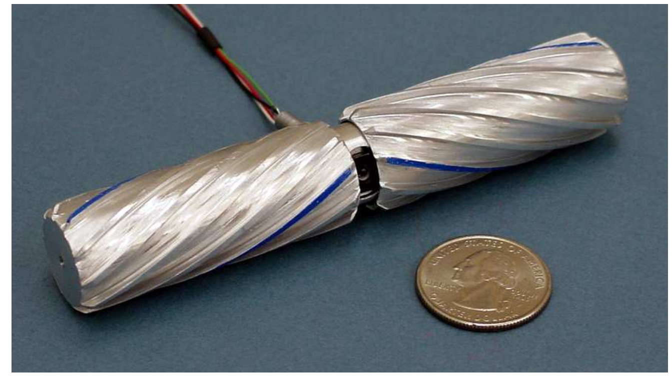
Redesigned Mobile Robot

- Traverse entire abdominal cavity
  - No tissue damage
  - Used for exploration

Crawler

Mobile Camera Robot

- Exploring abdominal cavity
- 2 port cholecystectomy possible
- Adjustable-focus camera
- Camera angles from any point

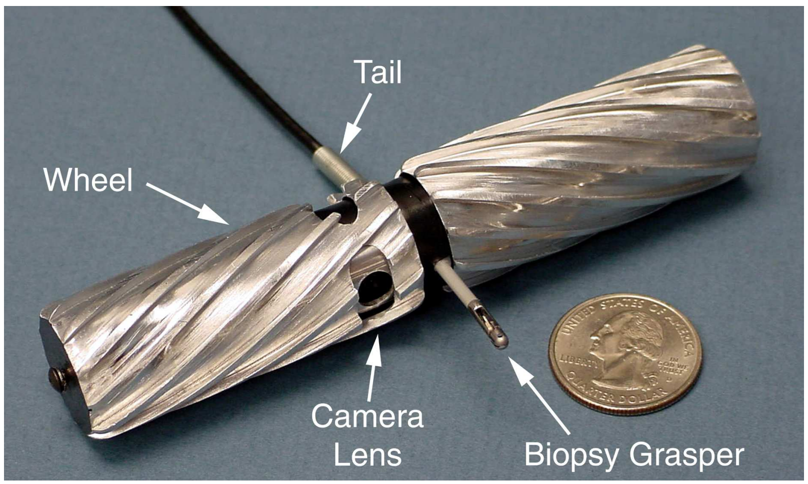


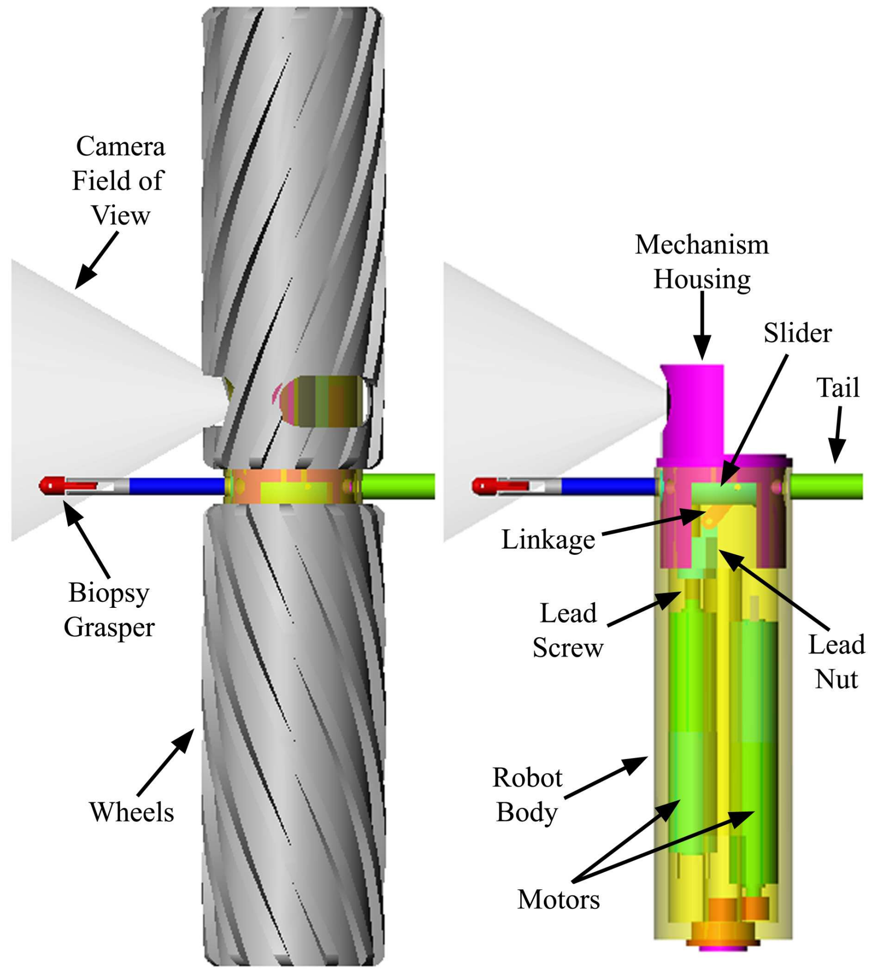
Mobile camera robot cholecystectomy

View from laparoscope

Biopsy Robot Design

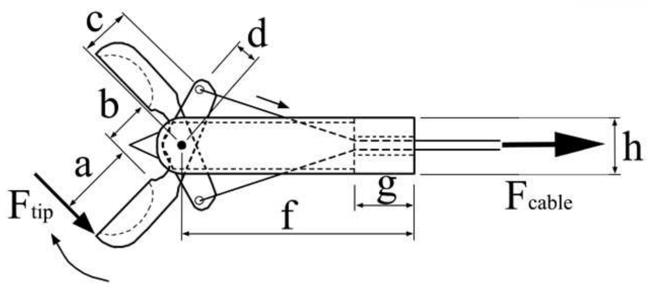
- Camera slots
- Adjustable-focus camera
- Novel mechanism

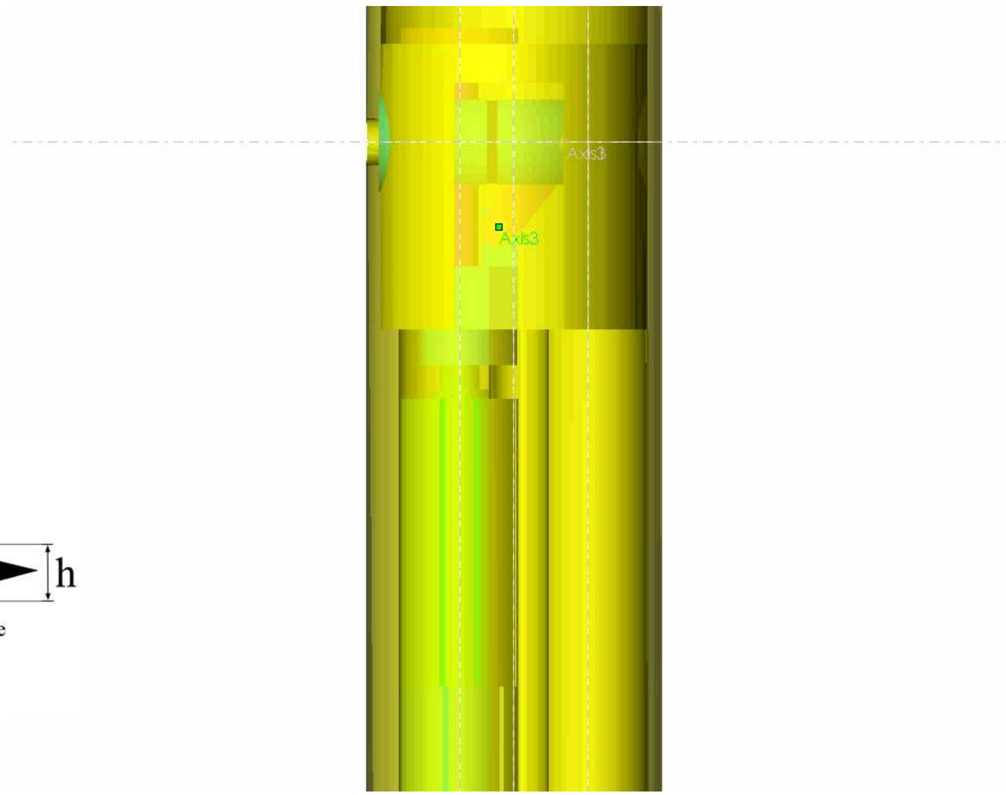




Mobile Biopsy Robot

- Sample tissue
- Clamp artery
- Apply large force





Biopsy Mechanism Design

In vivo Testing

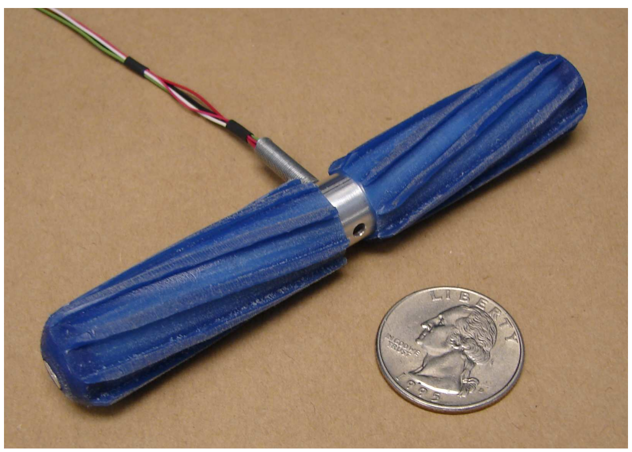
- Mobility on abdominal organs
- Sampled liver
- Retrieved sample after extraction
- Demonstrated a one port procedure

Laparoscope view

Mobile biopsy robot view

Current Efforts

- Mobile Wireless Camera/Biopsy Robot
- NOTES robot
- Mobility in blood filled cavities

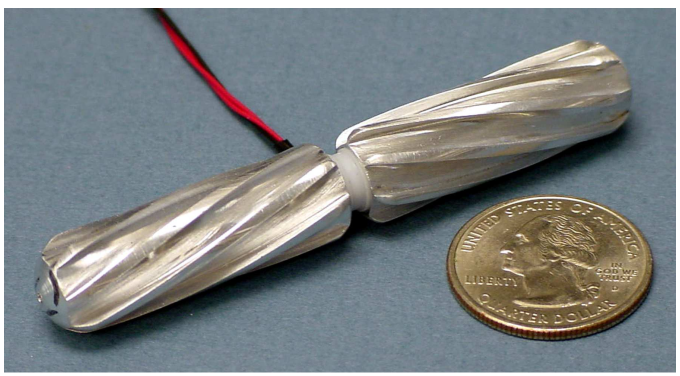


MRC Test

University of Nebraska

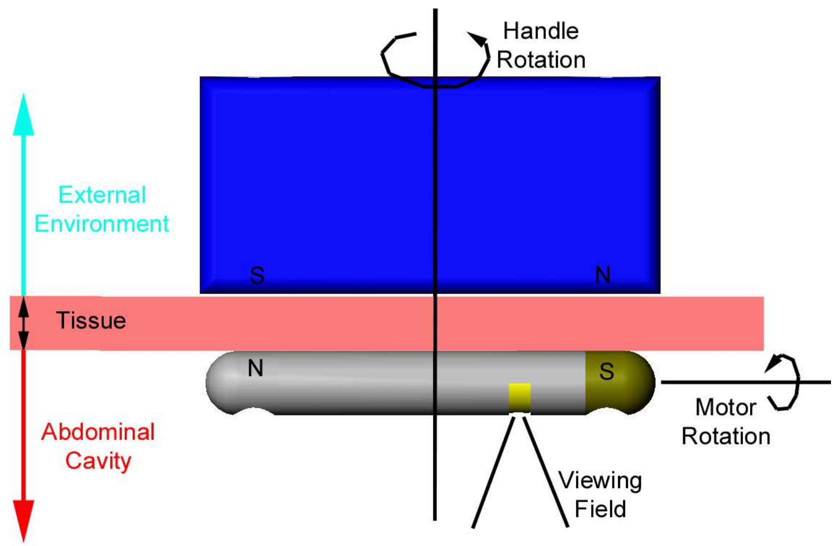
NOTES Progress

- Natural Orifice Transgastric Endoscopic Surgery (NOTES)
- Incision-less surgery
- Multiple robots



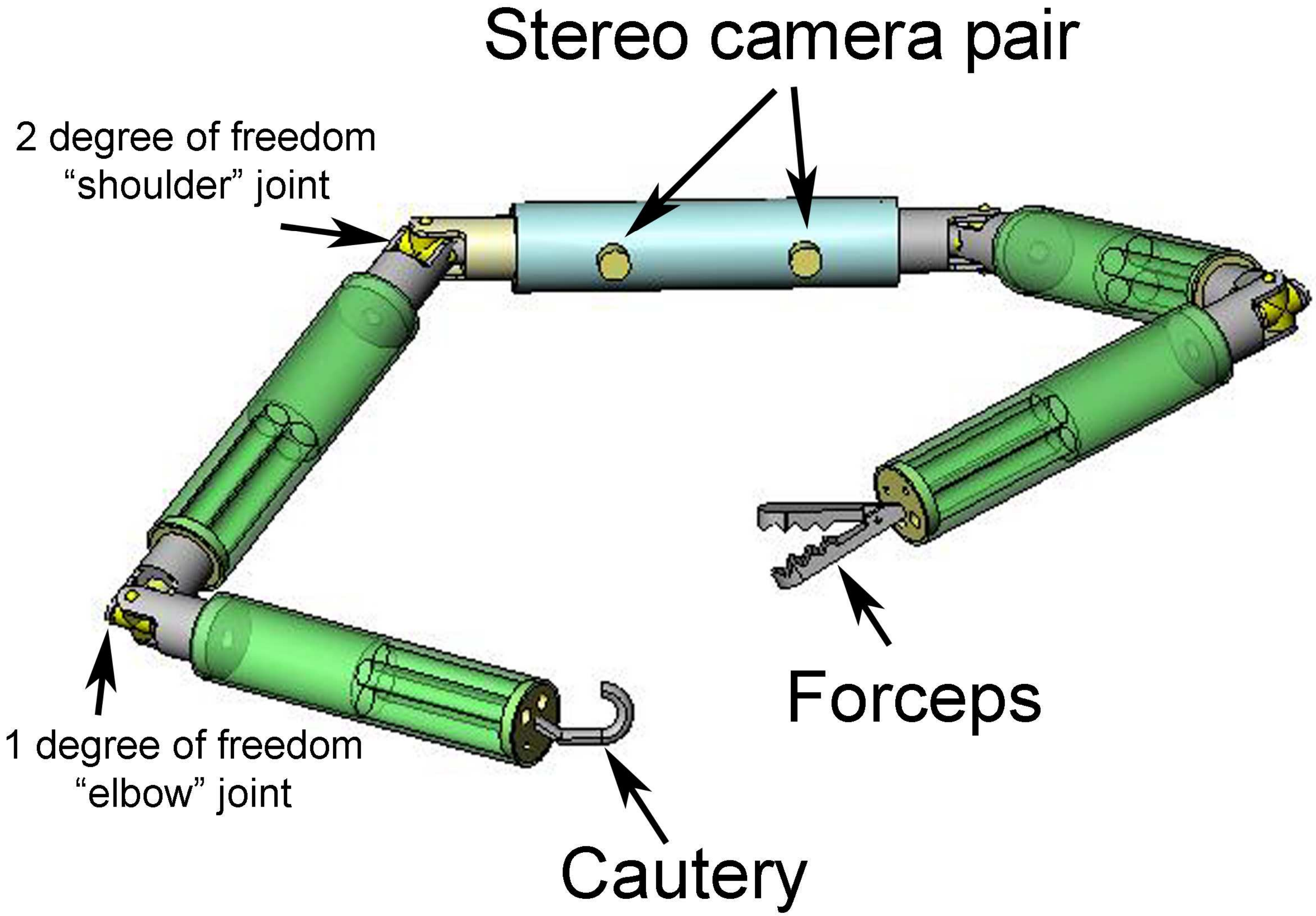
Mobile NOTES

Ceiling Pan/Tilt Camera Robot



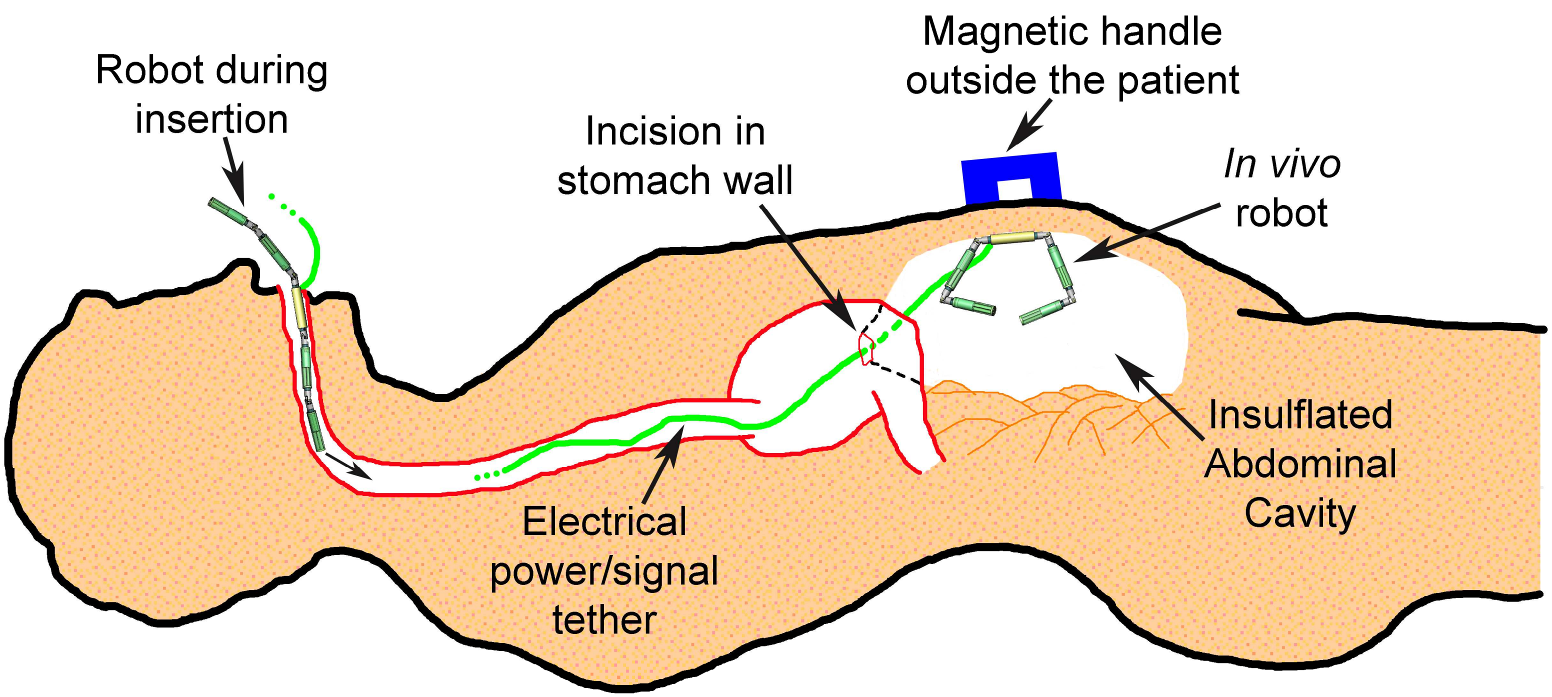
CPT Test

NOTES Robot

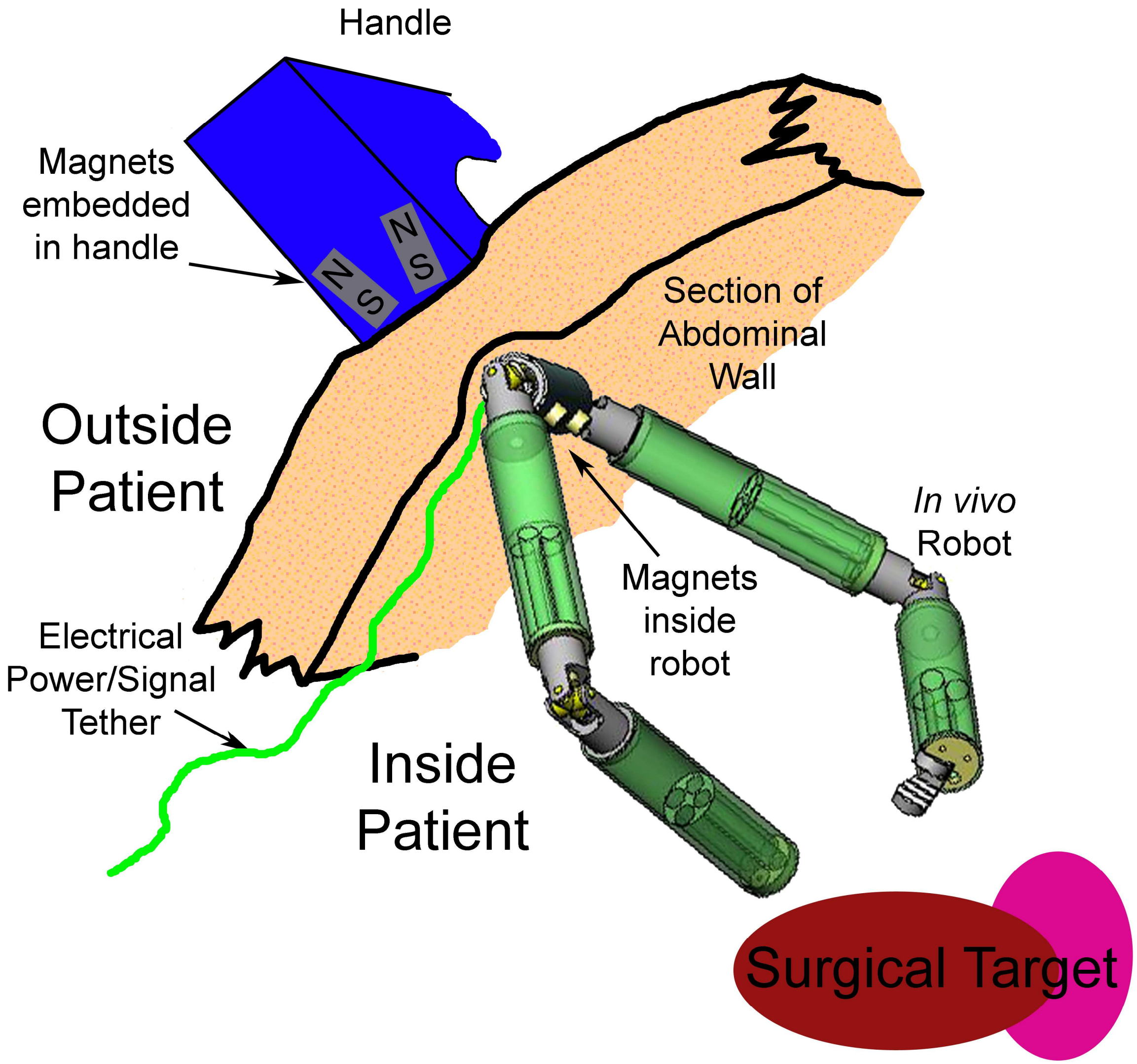


Stereo camera pair
2 degree of freedom
"shoulder" joint
1 degree of freedom
"elbow" joint
Forceps
Cautery

Natural Orifice Surgery



Use of a NOTES Robot



The Future

- Battlefield ops with portable imaging, path planning, automated/programmed surgery
  - Insert this into a heavily bleeding wound and have the robot seek out the source of the bleed and stop it.
- SLAM - Simultaneous Localization And Mapping
  - Include other modalities (CT, MRI, Ultrasound, X-ray)
- Depth and range mapping from stereovision
- Path and surgical planning using CT and MRI
- Semi-automated and automated processes

Questions

http://robots.unl.edu

http://www.unmc.edu/mis

Symbolic Motion Planning for Highly Maneuverable Robots

Emilio Frazzoli

Aeronautics and Astronautics

Massachusetts Institute of Technology

Workshop on

Mobility and Control in Challenging Environments

October 6, 2006

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Aerospace Robotics and Embedded Systems Laboratory

Motivation

MIT Acrobatic Helicopter ('01)

UCLA Golem 2 (DGC '05)

UCLA UAV Fleet ('06)

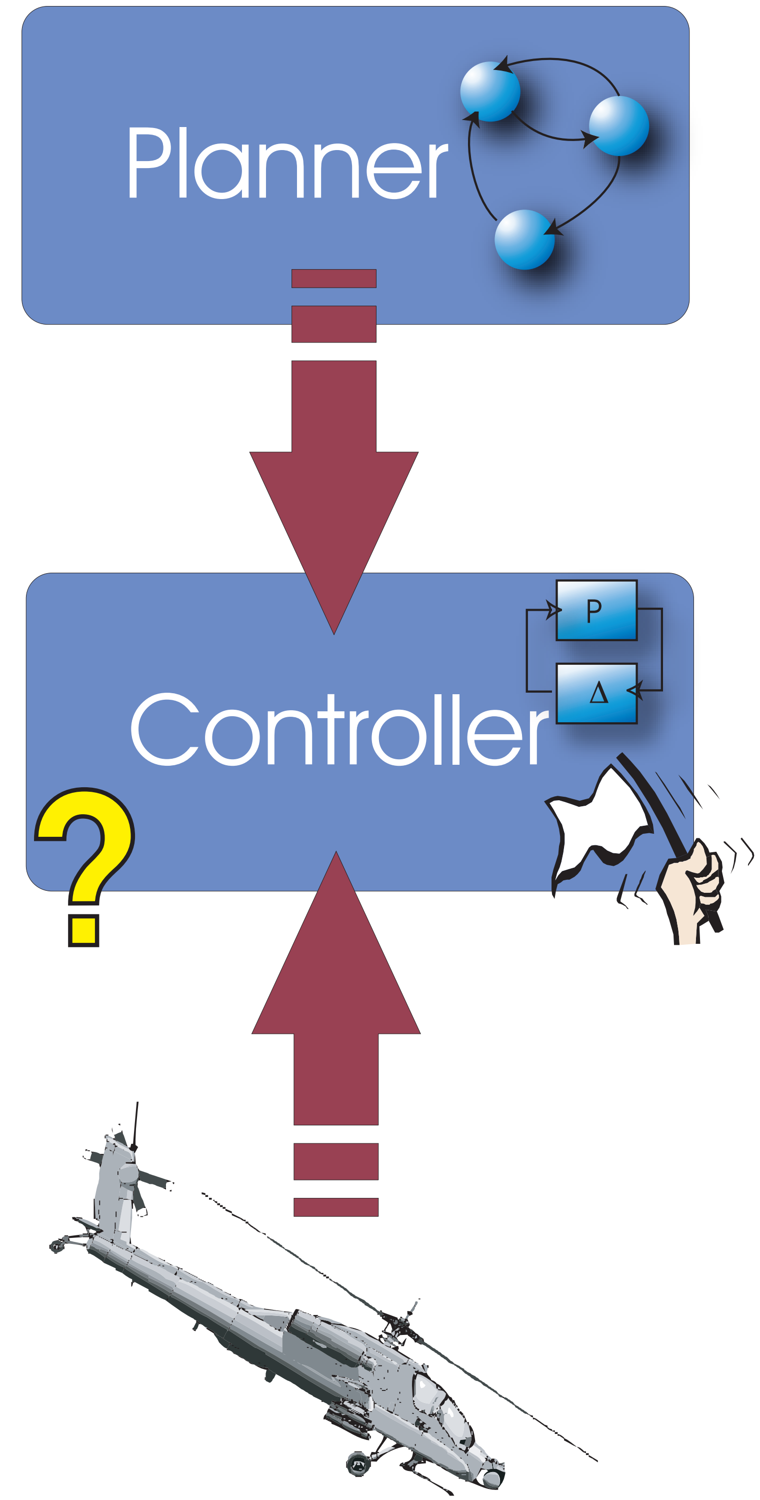
- Allow autonomous vehicles to push the boundaries of their operational envelope: fly/drive fast, react quickly to external events, etc.
  - critical ability for robotic vehicles and UAVs in uncertain/dangerous/hostile environments.
- Beyond the capabilities of "traditional" control design techniques.
  - New modeling/design paradigms needed.
- General applicability:
  - Aircraft, Spacecraft, Ground robots, Sailboats, Swimming robots etc.

The basic intuition

- Human pilots fly acrobatics combining well-practiced “maneuvers,” or elementary behaviors.
- Can we build a mathematically sound framework for motion planning and control based on this idea?

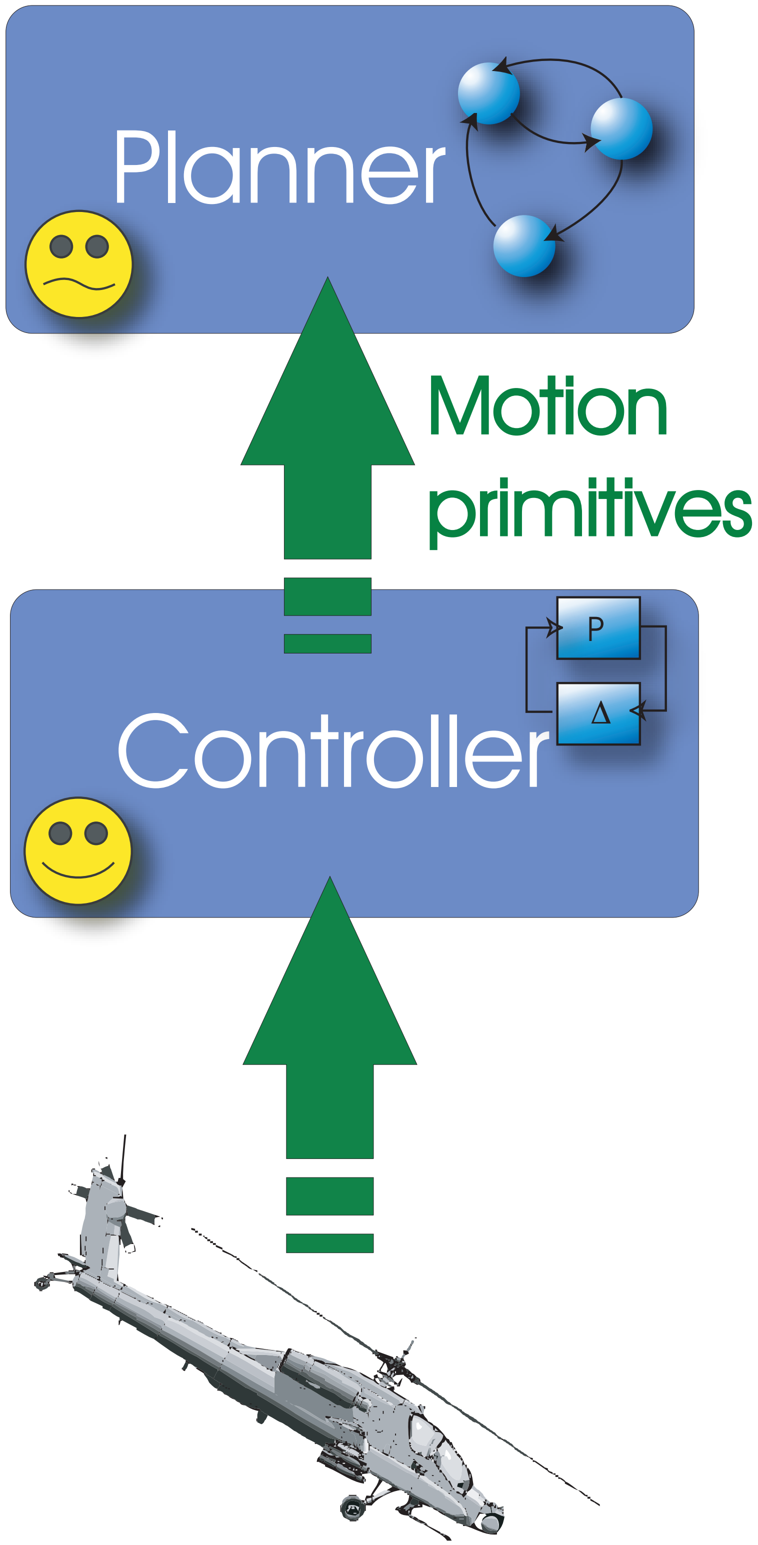
Hierarchical decomposition 1/2

- A hierarchical structure is desired, hiding (by "abstraction") unnecessary details at the planning level.
- The common approach:
  - Choose a priori a simplified, convenient, model of the system dynamics for the higher layers and force it upon the lower (control) layer. (e.g., discrete modes, kinematic models, piece-wise polynomial paths, etc.)
- Guarantees (safety, stability, performance) on the behavior of the system do not transfer from one level the others.



Hierarchical decomposition 1/2

- A new approach:
  - Choose a subset of actual trajectories of the system, and allow motion planning only as a combination of such motion primitives, or closed-loop behaviors.
- **Pro**: consistent hierarchical system. Any command from the planned can be executed by the controller (is a “natural trajectory”)
- **Pro**: model-free, no need to know the differential equations describing the dynamics.
- **Con**: over-constraining of trajectories. Only allow behaviors which can be generated through the sequential combination of known primitives.



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Problem formulation

Consider a time-invariant dynamical control system $\mathcal{S}$:

$$\dot{x}(t) = f(x(t), u(t)),\ x \in \mathcal{X}, u \in \mathcal{U} \subset \mathbb{R}^m \tag{1}$$

and its flow under a (possibly closed-loop) control law: $\mu : [0, t_f] \times \mathcal{X} \to \mathcal{U}$

$$x(t) = \varphi_\mu(x(0), t) \tag{2}$$

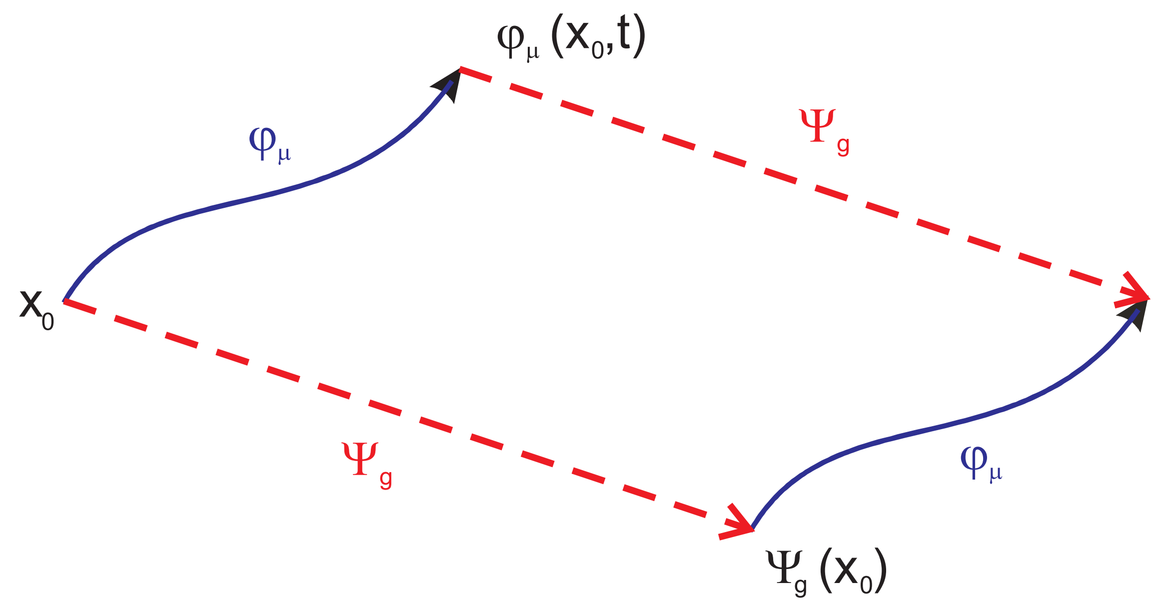
Given an initial condition x_0 and a target x_f, find a (piecewise continuous) control law μ such that:

1. $\exists t_f \geq 0 : x_f = \varphi_\mu(x_0, t_f)$, **[dynamics]**;
2. $C(x(t), \mu(t, x(t))) \leq 0,\ \forall t \in [0, t_f]$ **[operational envelope]**;
3. $J(x, u) = \int_0^{t_f} \gamma(x)$ *is minimized* **[performance criterion]**.

Symmetry

- The complexity of the motion planning problem in general is daunting.
- **Exploit geometric structure** $\Rightarrow$ reduce the problem to a form of **kinematic inversion** (without introducing simplifications in the model.)
- **Symmetry**, i.e., invariance with respect to a class of transformations on the state, is a **fundamental geometric property of many systems of interest**, e.g. mobile robots and autonomous vehicles.

Motion Primitives



- **Motion primitive**: equivalence class of finite-time integral curves of (1) $t \in [0, T] \mapsto (x(t), u(t))$, modulo:
  - Time translations
  - Actions of $\mathcal{G}$.
- Note:
  - If $F(x, u) = F(\Psi(g, x), u)$, **feasibility** with respect to operational envelope constraint is uniform on motion primitives.
  - If $\gamma(x, u) = \gamma(\Psi(g, x), u)$, the **cost** of a motion primitive is uniform on motion primitives (e.g. minimum-time, -length, -energy).

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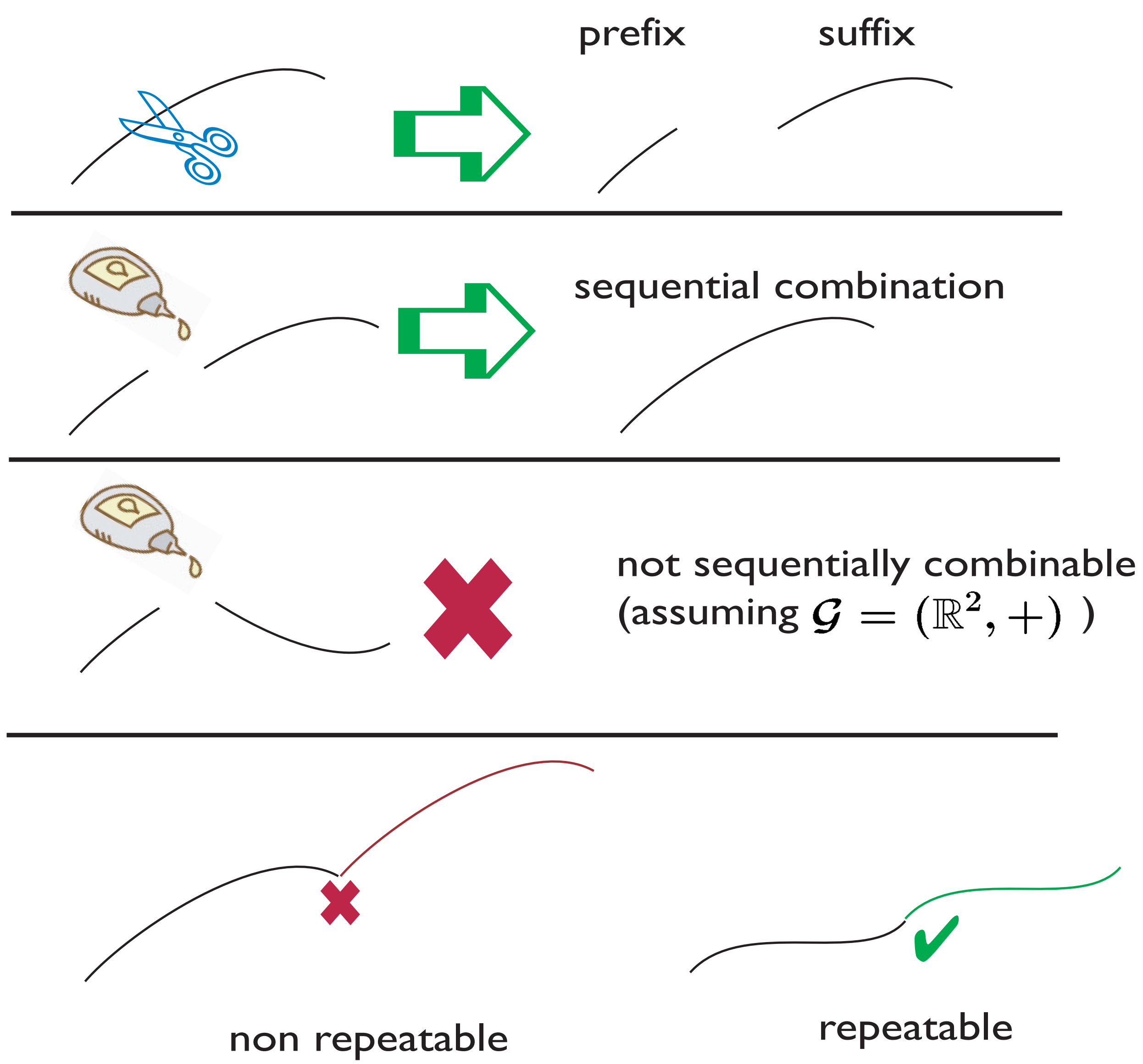
Operations on primitives

- **Prefix, suffix:** **cut** a motion primitive into two pieces. Each piece is still a motion primitive.
- **Concatenation:** **join** two motion primitives. This operation is possible only under certain **compatibility** conditions.
- **Repeatable primitive:** A motion primitive which can be concatenated with itself.



Finite vs. finite-description libraries

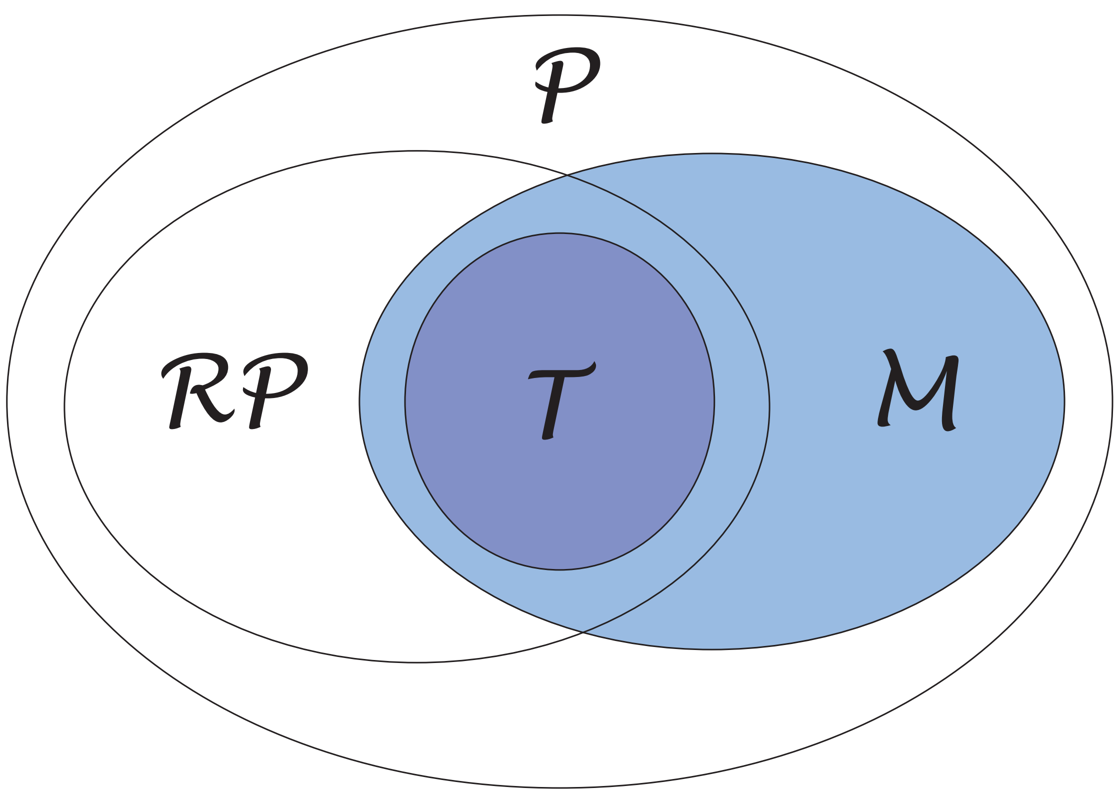
- A finite collection of primitives leads to a discrete reachable set (e.g., a lattice).
- Even though the lattice can be made arbitrarily dense, the length of motion plans may become unbounded.
- Look for families of continuously-parameterized primitives: maintain a ”finite description,” while effectively considering an uncountable number of primitives.

Classification of Primitives

- **Trim Primitive**: a non-trivial repeatable motion primitive whose prefixes and suffixes are repeatable.
  - **Lemma**: The closure of a trim primitive under prefix, suffix and concatenation is a connected one-parameter semigroup with identity.
  - **Theorem**: A motion primitive α is a trim primitive if and only if it can be written as $\alpha(t) = (\Psi(\exp(\xi_\alpha t), x_\alpha), u_\alpha)$, with $\xi_\alpha \in \mathfrak{g}$.
- A trim primitive is a **steady-state trajectory**. The nature of possible trim primitives depends on the symmetry group:
  - **Sailboats** ($\mathcal{G} = \mathbb{R}^n \times O(1)$) : straight lines;
  - **Car-like robots** ($\mathcal{G} = SE(2)$): arcs of circles;
  - **Aircraft-like robots** ($\mathcal{G} = SE(2) \times S^1$): arcs of helices with a vertical axis.

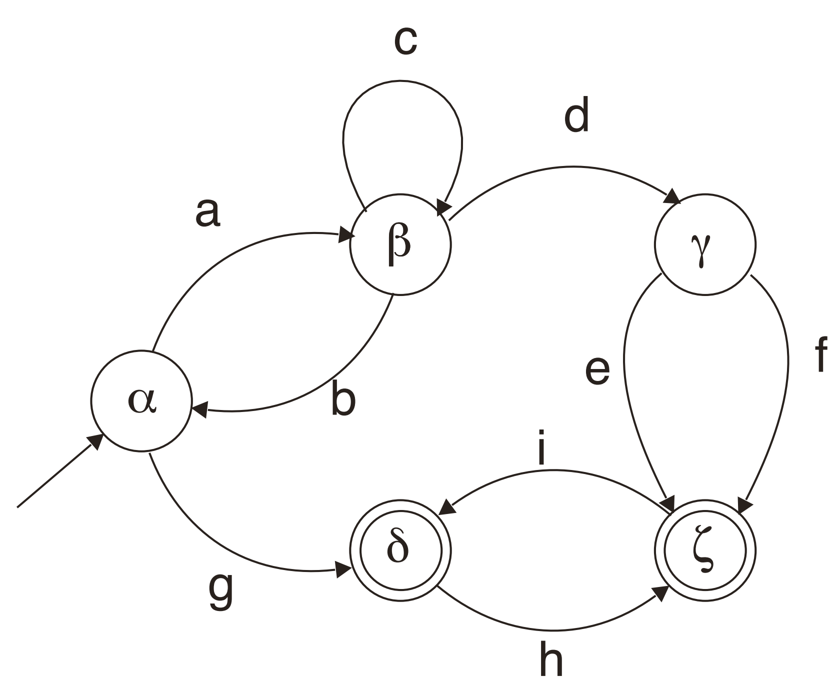
Classification of Primitives 2/2

- **Maneuver**: a non-trivial motion primitive which can be concatenated, from the left and from the right, with a trim primitive.
- Formal definition of “maneuver:”
  - *Well-defined pre- and post-conditions;*
  - *A common interface for concatenation.*



A formal language for motion description

- Σ: An **alphabet** composed of a *finite number of maneuvers*.
- ω: **words** of the language $L(\mathrm{MA}) \subseteq \Sigma^*$.
- The language $L(\mathrm{MA})$ is the set of all strings accepted by a finite-state machine, called a Maneuver Automaton. $MA = \{Q, \Sigma, \delta, q_0, F\}$
  - Q: a set of states. In our case, a set of trim primitives.
  - Σ: the already-defined alphabet.
  - $\delta : Q \times \Sigma \rightarrow Q$: a transition function.
  - q_0, F: resp. an initial state and a set of final, or accepting states.



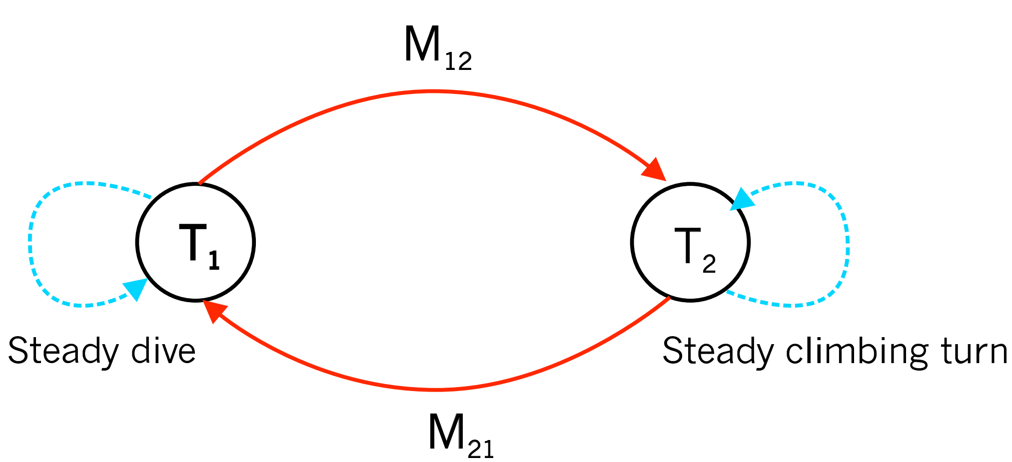
Motion Planning

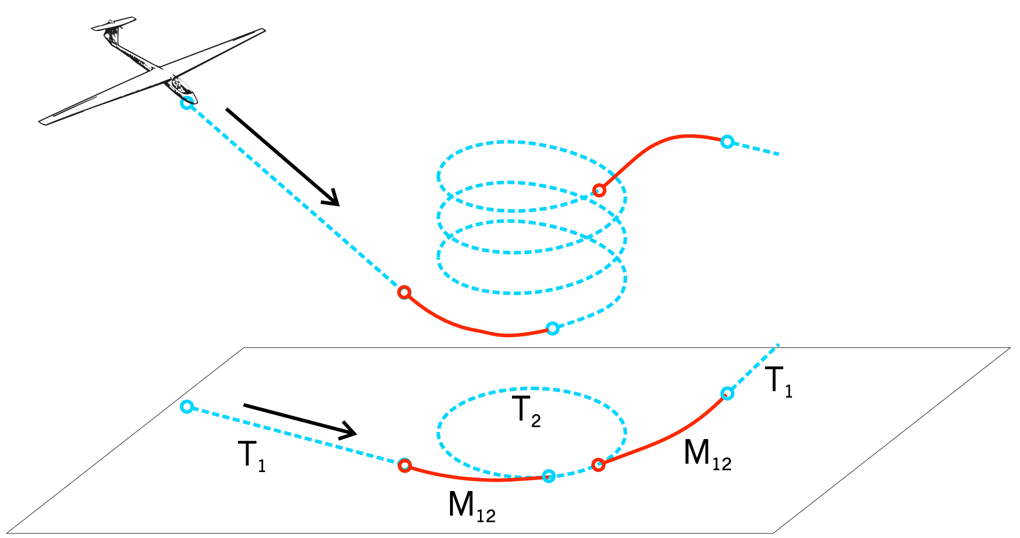
- A **Maneuver Sequence** is a word $\omega \in L(MA)$, i.e., a path on the Maneuver Automaton directed graph. It corresponds to the primitive

$$\omega = \pi_1 \pi_2 \ldots \pi_{N(\omega)}.$$

- A **Motion Plan** is a pair (ω, τ), where τ is a vector of $N+1$ non-negative **coasting times**, corresponding to a primitive of the form

$$\omega_T = \alpha_1(\tau_1)\pi_1\alpha_2(\tau_2)\pi_2 \ldots \pi_N \alpha_{N+1}(\tau_{N+1}).$$





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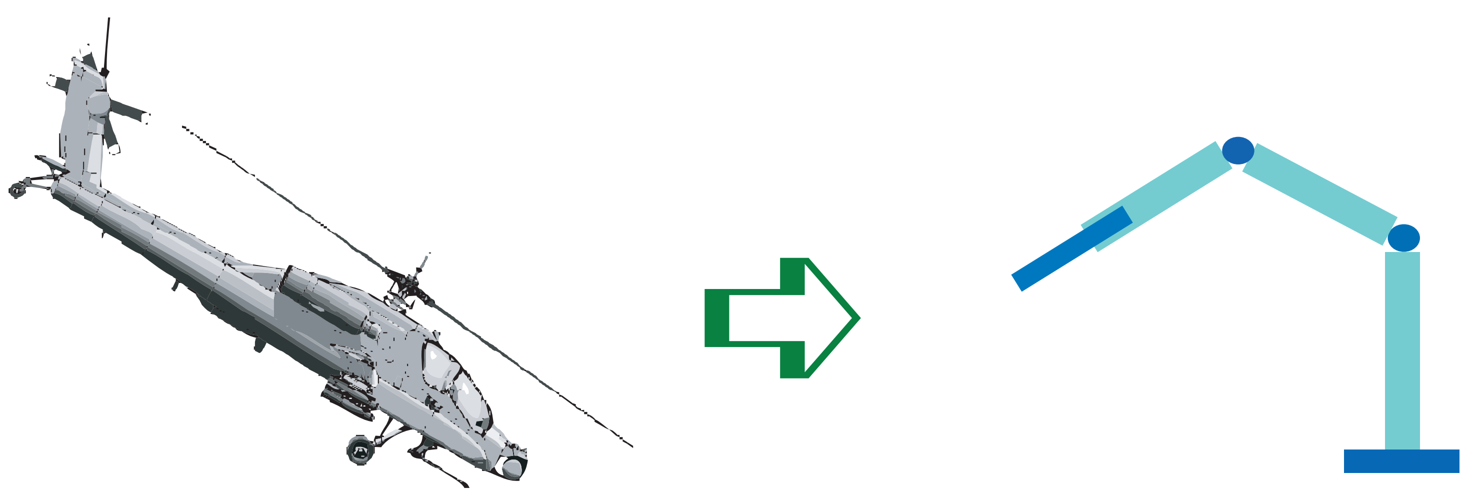
Kinematic reduction

- Given an initial condition $x_0 = \Psi(g_0, x_{\alpha_1})$, the final state after a motion plan (ω, τ) is $x_f = \Psi(g_f, x_{\alpha_{N+1}})$, where:

$$
\begin{aligned}
g_f &= g_0 \left[\prod_{i=1}^{N} \exp(\xi_{\alpha_i} \tau_i) g_{\pi_i} \right] \exp(\xi_{\alpha_{N+1}} \tau_{N+1}) \\
&= g_0 g_\omega \exp(\eta_1 \tau_1) \ldots \exp(\eta_{N+1} \tau_{N+1})
\end{aligned}
$$

- The expression above has the structure of a (forward) kinematic map.
- Motion planning problems for complicated dynamical systems can be solved through **kinematic inversion**!



(Sub-) Optimal Motion Planning

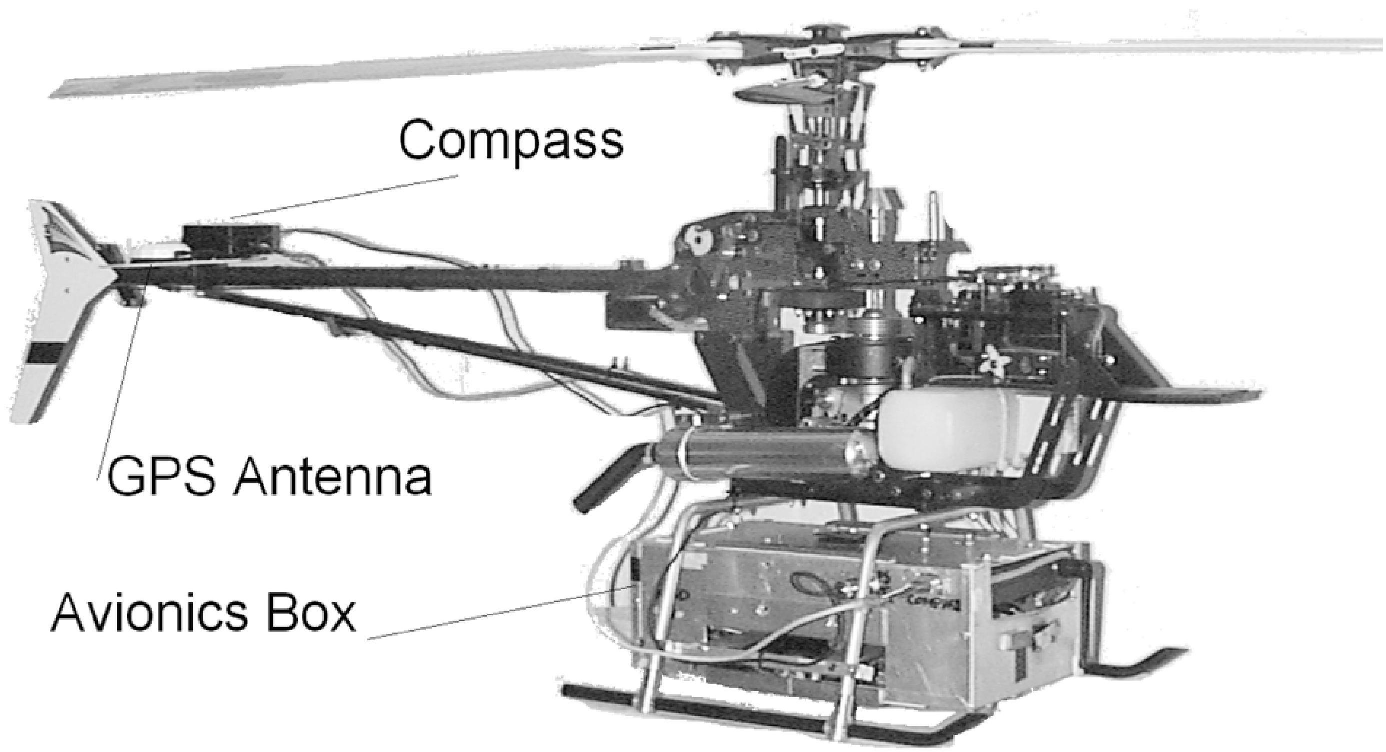
- An approximation to the optimal motion planning problem can be obtained efficiently by restricting allowable motions to the concatenation of known primitives.
- Using the MA language, the optimal motion planning problem is recast as:

$$\begin{aligned}(\omega, \tau)^* = \;& \arg\min \sum_{i=1}^{N(\omega)} (\Gamma_{\pi_i} + \gamma_{\alpha_i}\tau_i) \\ \text{s.t.: }\; & \prod_{i=0}^{N(\omega)} \exp(\eta_i \tau_i) = (g_0 g_\omega)^{-1} g_f \\ & \tau \geq 0.\end{aligned} \tag{5}$$

- **Hierarchical motion planning:**
  - **Combinatorial component:** Choice of maneuver sequence ω
  - **Kinematic inversion** to compute coasting times τ.

Example: Aerobatic helicopter

- Application of the proposed motion planning methodology to a realistic model of an X-Cell .60 SE small-size helicopter.
- The helicopter is equipped with an on-board CPU and a full avionics suite, including solid-state angular rate sensors and accelerometers, GPS unit, compass and air data system.
- The helicopter dynamics have been modeled using a combination of first-principle modelling and system identification



Methodology

- Possible approaches to the design of a motion library:
  - model-based optimal control design;
  - analysis of human-piloted flight data;
  - analysis of closed-loop behavior using “simple” feedback controllers.
- For the sake of clarity, we will consider a very small library of motion primitives, containing only four trim primitives, and seven maneuvers;
- In practical application, the choice of the number of motion primitives to include in the library is a matter of trade-off between achievable performance—and planning completeness—and computational complexity; a typical library can contain hundreds of primitives. The planner in [Frazzoli *et al.* ’02] used 625 primitives, while maintaining real-time computation capabilities.

Invariant tracking

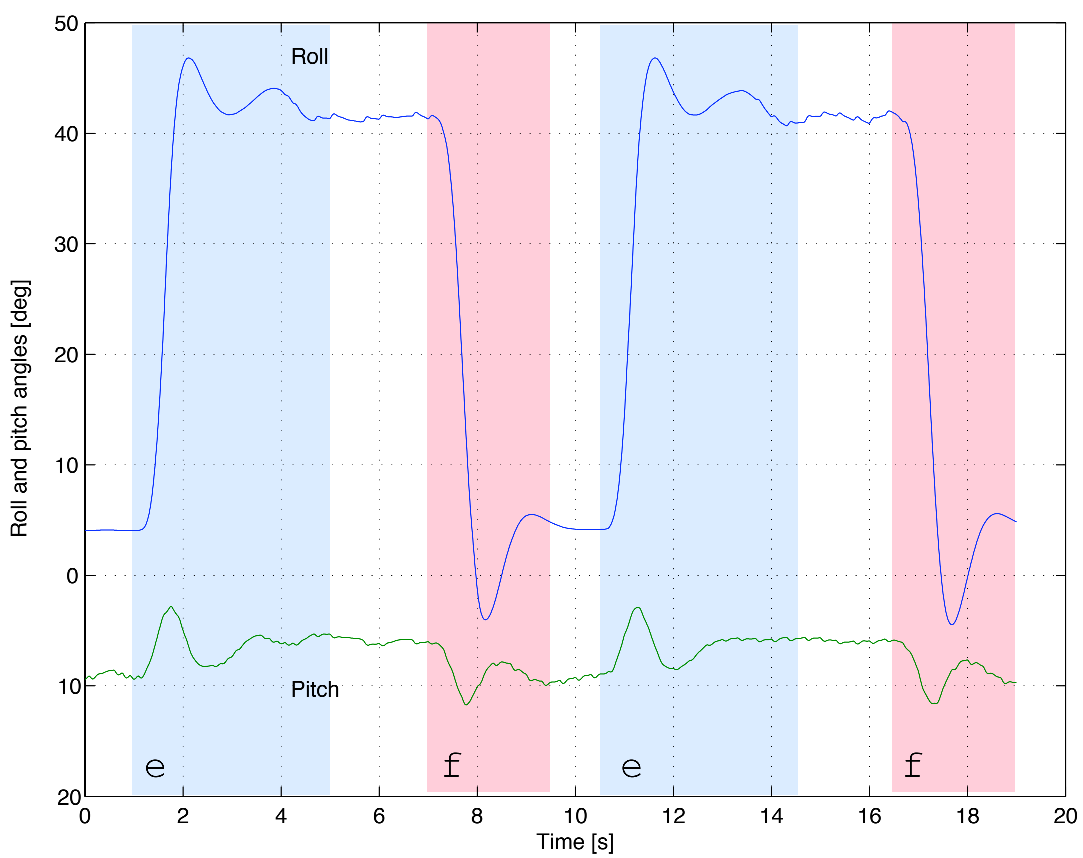
- Let us consider the $\mathcal{G}$-invariant system $\dot{x} = f(x, u)$; if the system is unstable, open-loop control is doomed to failure.
- Close the loop with a (static) feedback controller, with reference $v \in \mathcal{V}$:

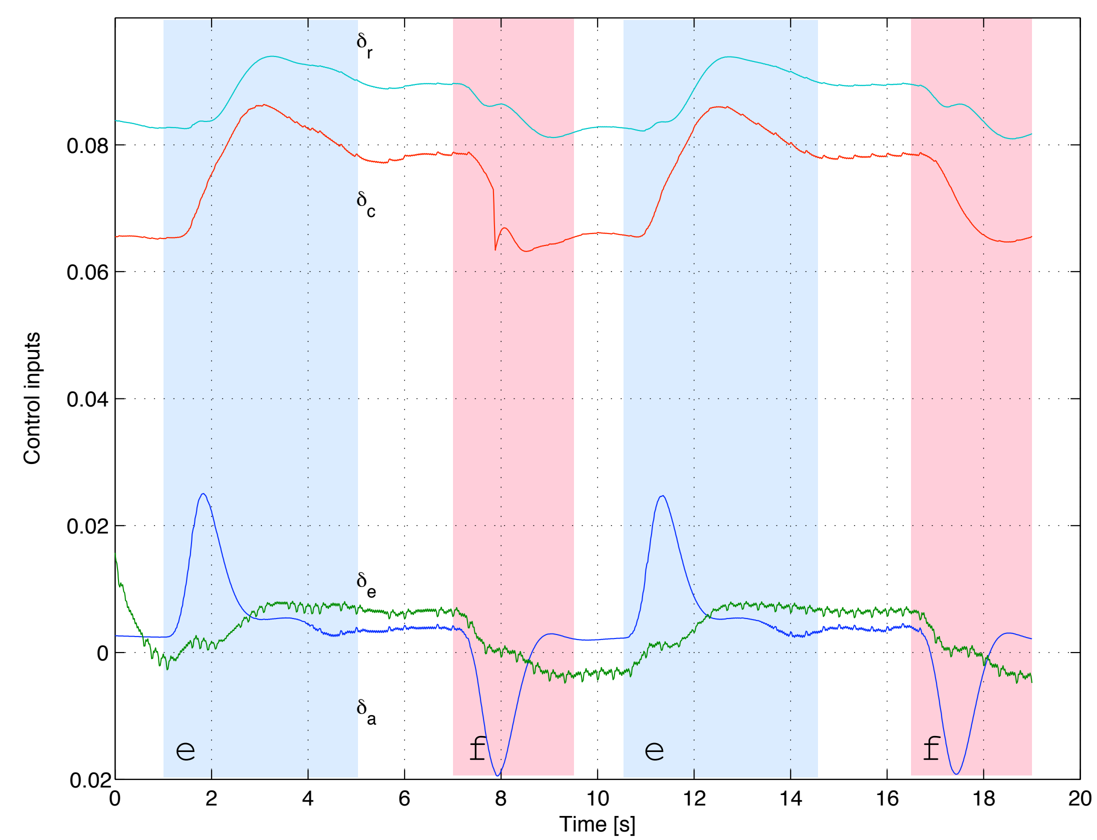
$$\mu : \mathcal{X} \times \mathcal{V} \to \mathcal{U}.$$

- The MA approach is applicable as long as:
  - the feedback preserves invariance,
    i.e. if $x = f(x, \mu(x, v)) = \tilde{f}(x, v)$ is $\mathcal{G}$-invariant, and
  - Closed paths on the MA lead to contraction mappings.
- Note that an open maneuver sequence is allowed
  to be ”destabilizing.”
- For the helicopter example, we used a ”backstepping on manifolds” approach introduced in Frazzoli et al, 2000, that satisfies the above assumptions (for appropriate choice of maneuvers).

Maneuvers

- Simple transitions between different trim primitives can be generated by commanding a transition, over a time T, in the velocity of the reference trajectory.
- The closed-loop behavior of the helicopter will provide a feasible trajectory achieving the desired velocity change.
- The choice of the time T determines the "aggressiveness" of the maneuver, and is tuned to achieve a fast response, without violating flight envelope constraints.





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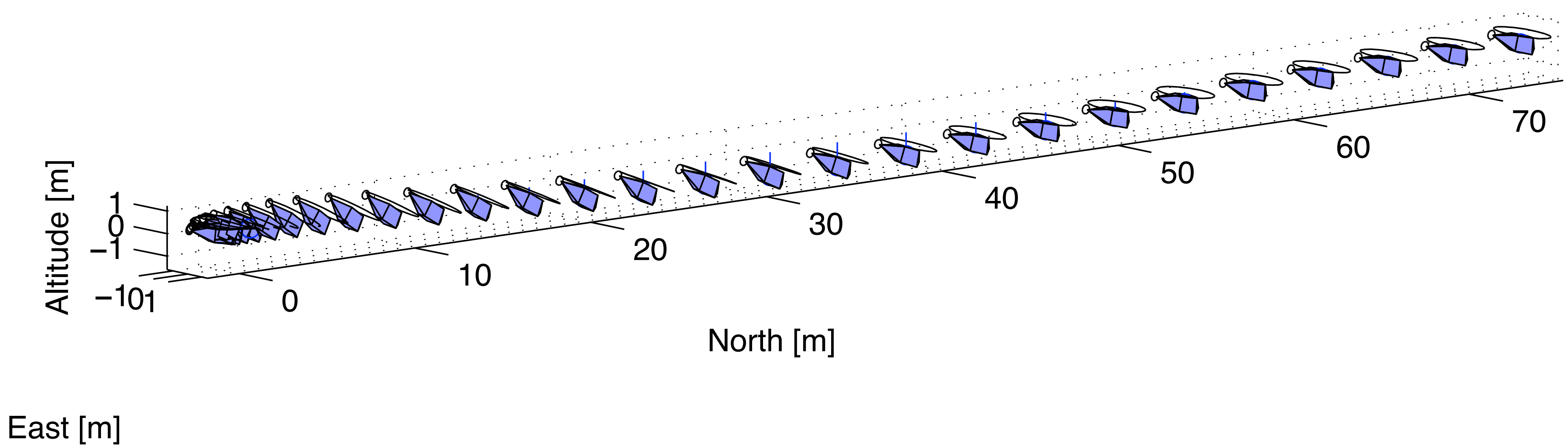
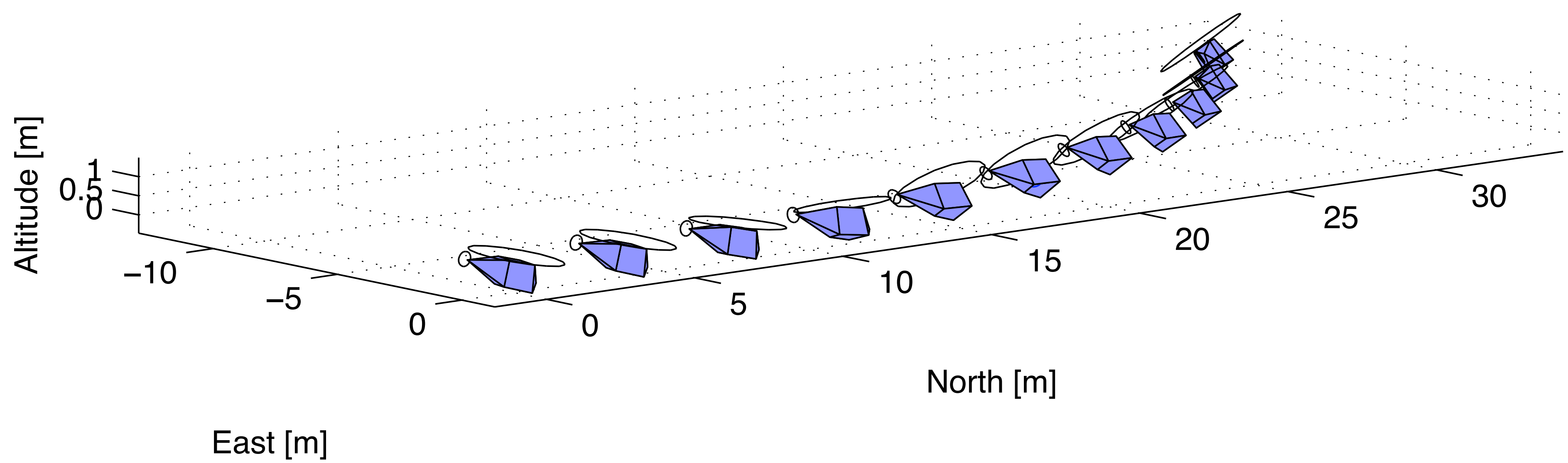
Maneuver Examples

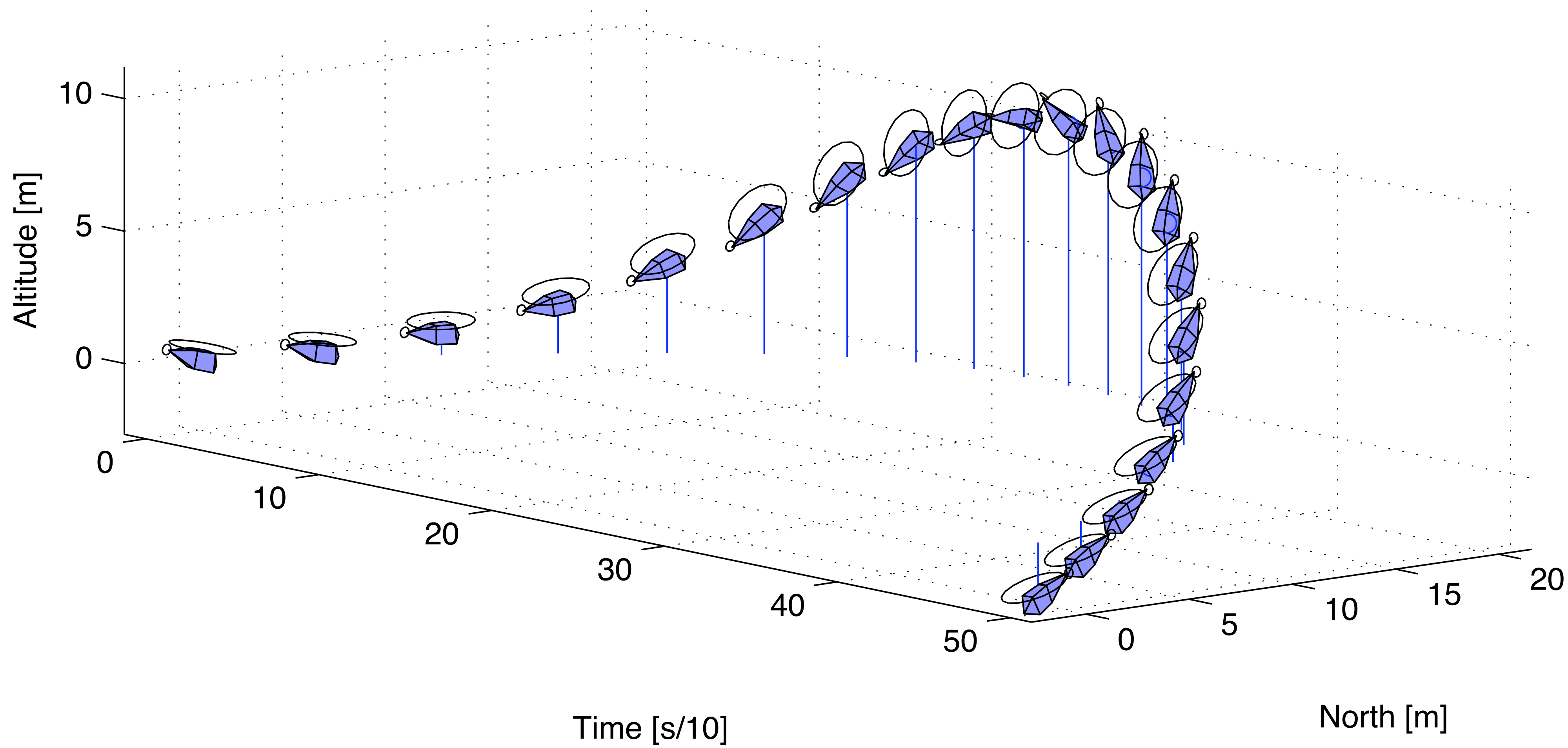


Transition from hover to forward flight



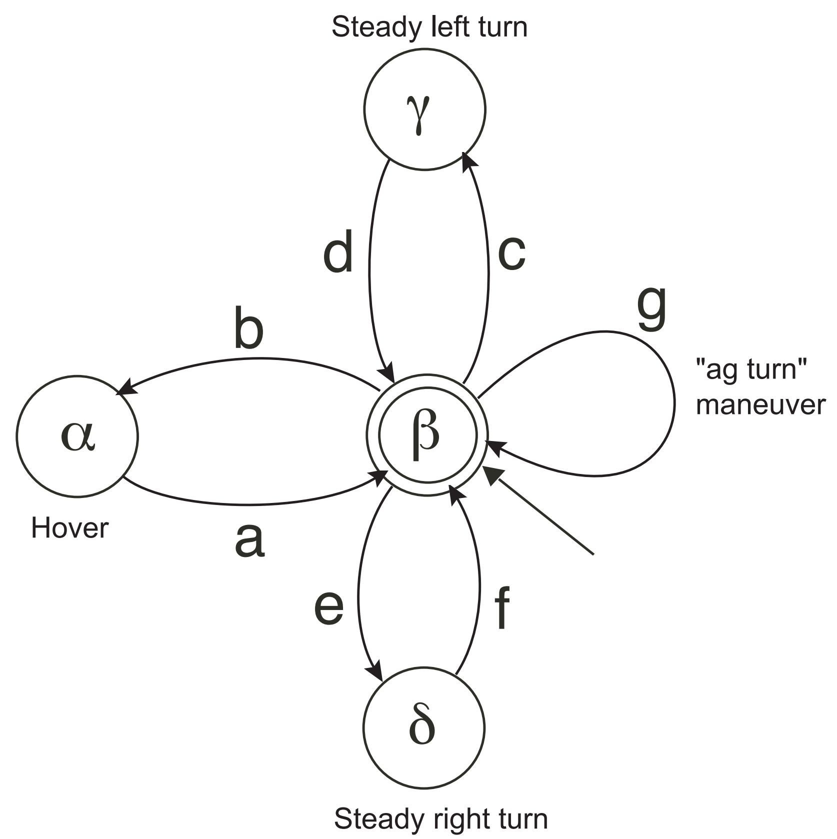
Transition from forward flight to steady turn to the left

Aerobatic Maneuver



Ag-turn (or Hammerhead)

Maneuver Automaton



ID	Pred	Succ	Duration [s]	Δp	$\Delta\psi[^\circ]$
a	α	β	7.5	(67.5, 0, 0)	0
b	β	α	5	(22.5, 0 0)	0
c	β	γ	4.5	(31.5, -41.7.0, 0)	-120.0
d	γ	β	2	(28.9, -6.6, 0)	-15.0
e	β	δ	4	(34.2, 34.9, 0)	105.0
f	δ	β	2.5	(36.1, 8.6, 0)	15.0
g	β	β	7.1	(-43.5, 0, 0)	180

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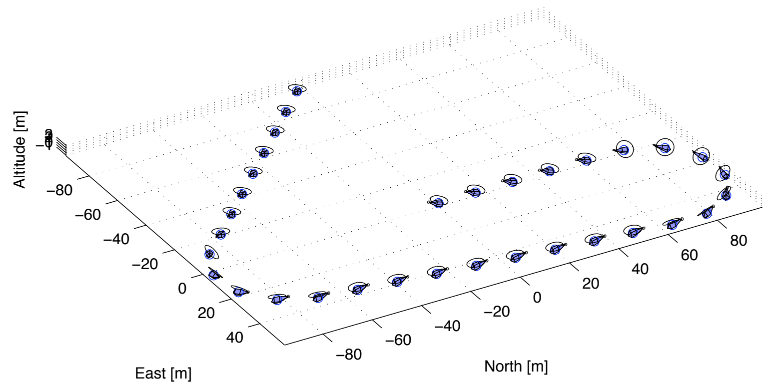
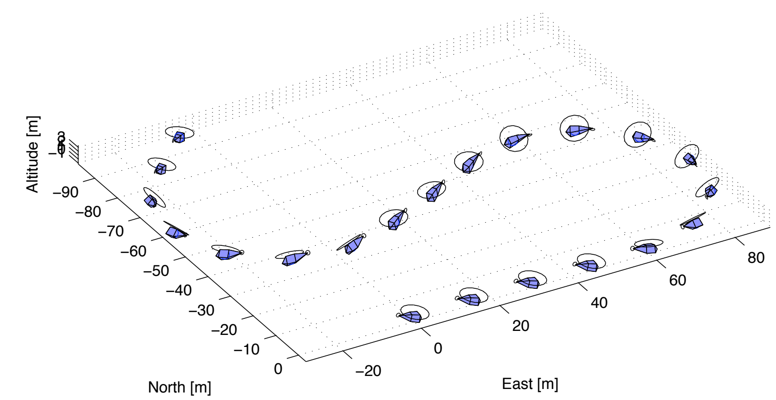
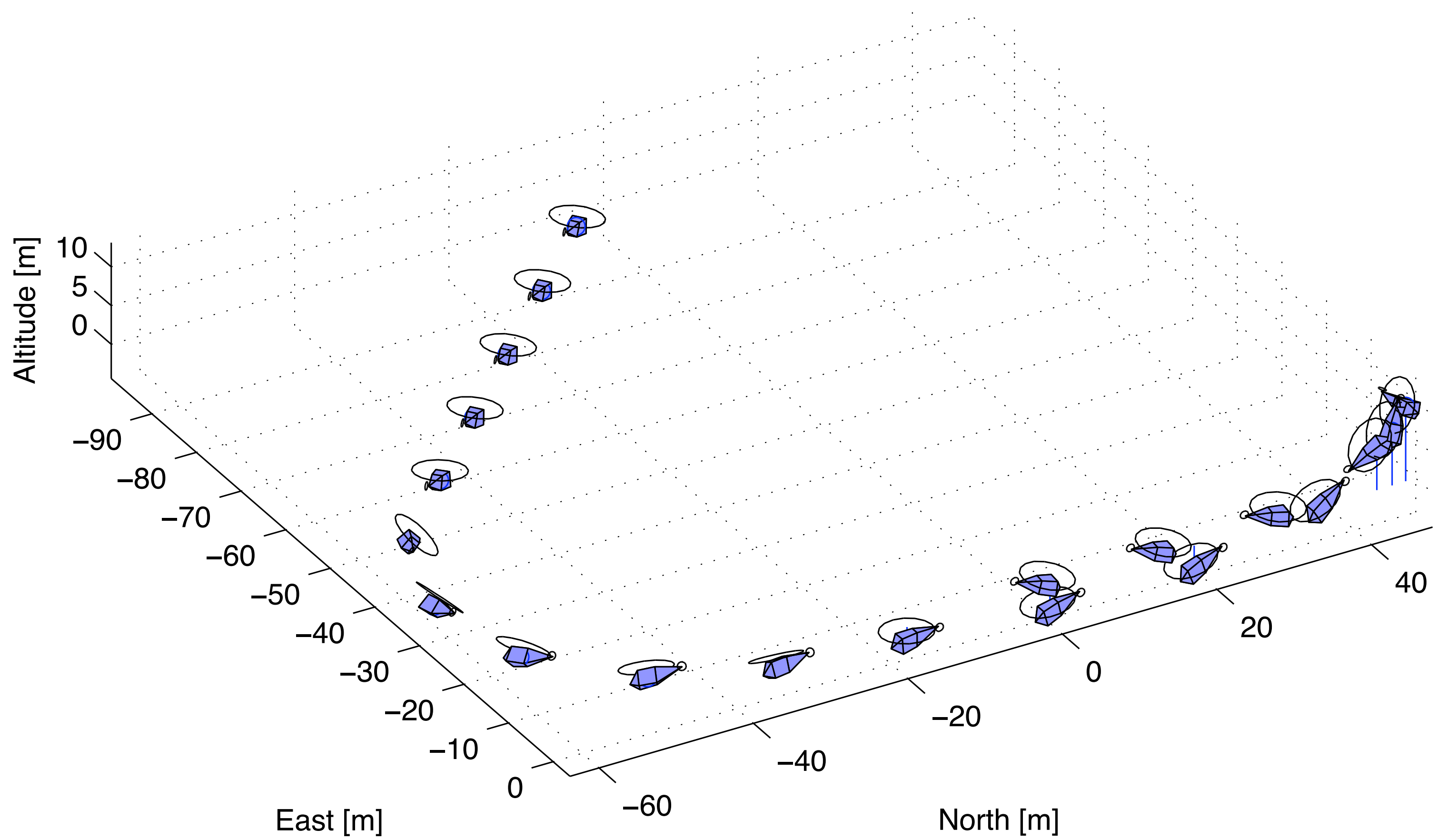
Search for Optimality







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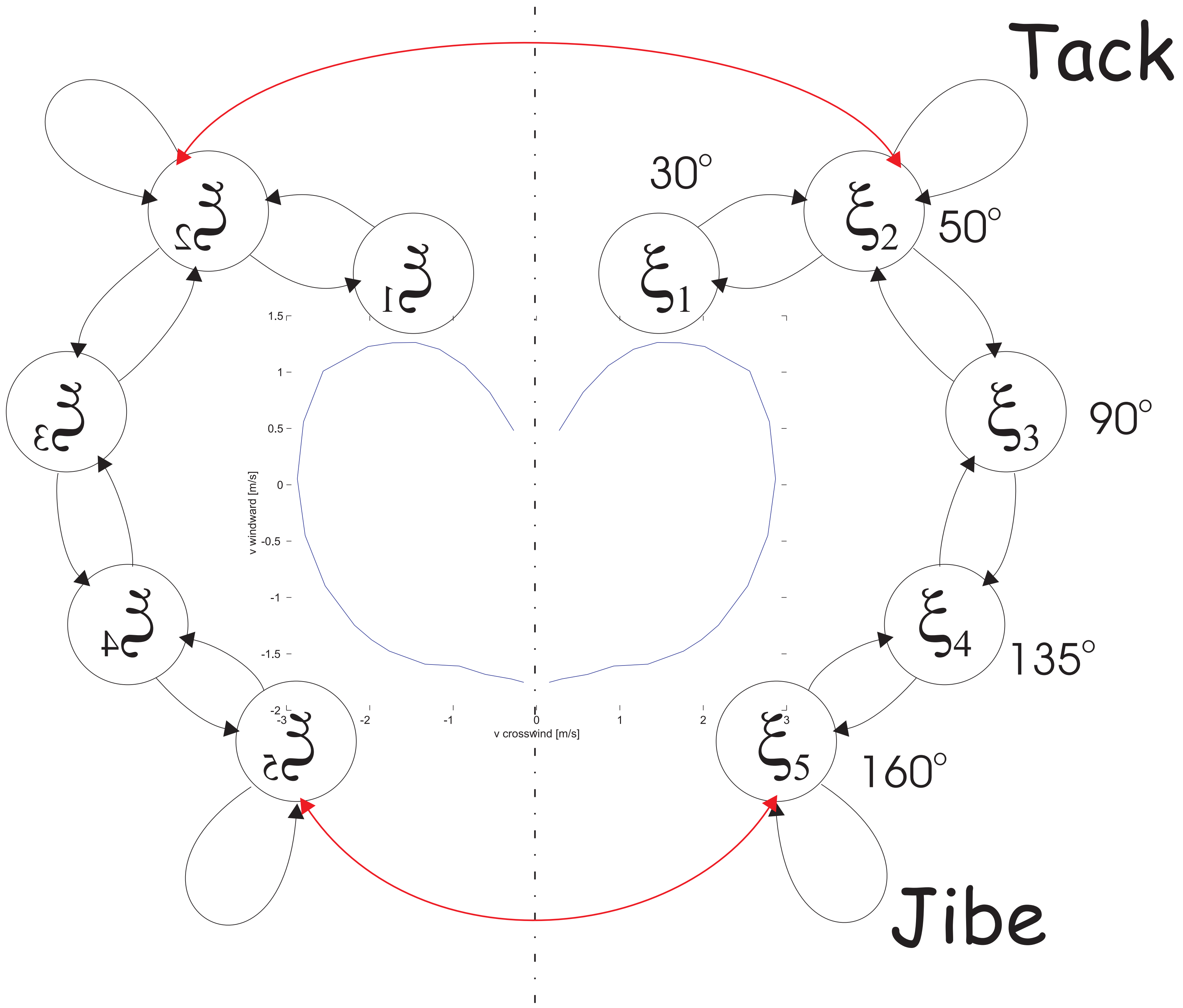
Match Racing

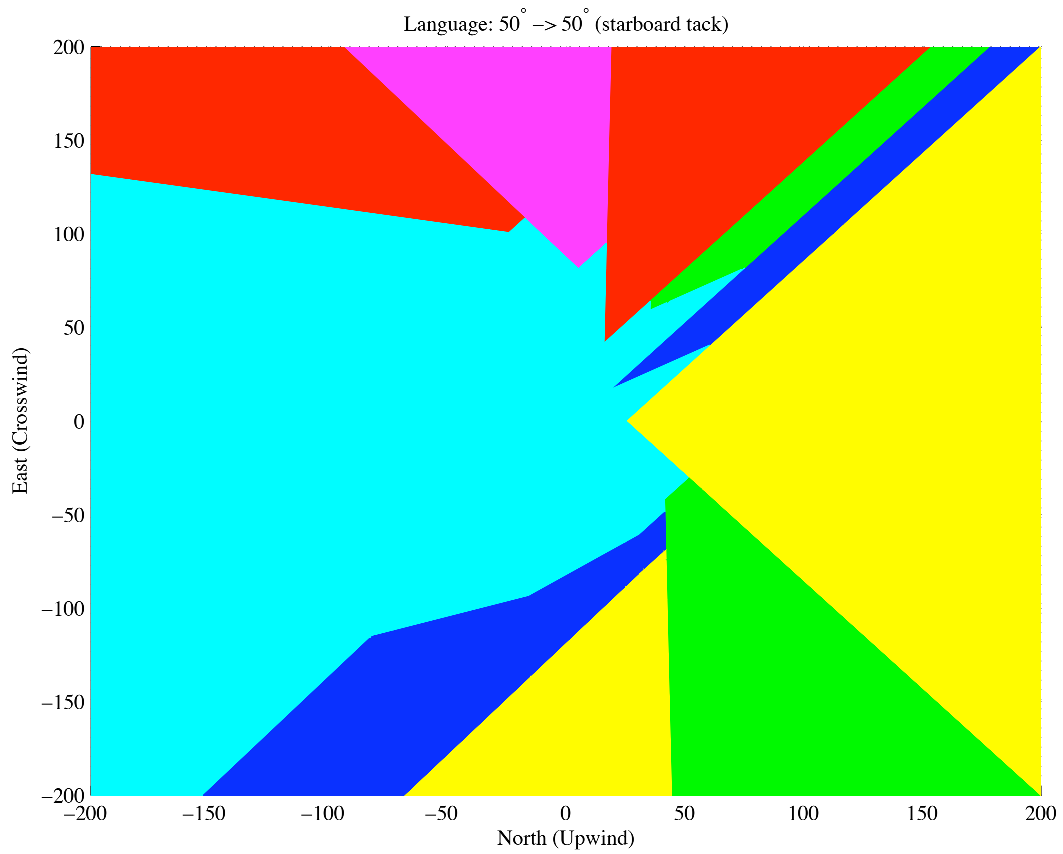
The sailor's problem

- **Problem:** Steer a **sailboat** between two waypoints in minimum time.
- **Dynamic model:** A sailboat can be modelled as a **hull** and three wings: the **sail**, the **keel**, and the **rudder**. Propulsive forces are generated by exploiting the relative motion of air and water.
- **Controls:**
  - **Tiller (rudder).** Positive if turning into the wind. Stall condition $|u_1 - \theta_{\text{water}}| < 17°$.
  - **Sheet (mainsail angle).** $u_2 \in [10°, 85°]$, note that $|\theta_{\text{sail}}| = \min(\theta_{\text{wind}}, u_2)$, i.e. the sheet can only pull the sail, cannot push it against the wind.
- Two **unconnected regions of operation**, i.e. starboard and port tacks (wind on either side of the boat).
- The system is invariant under translation and reflection about the wind axis $\Rightarrow$ the symmetry group is not connected.

MA design


Tack
Jibe
30°
50°
90°
135°
160°
ξ_1
ξ_2
ξ_3
ξ_4
ξ_5
v windward [m/s]
v crosswind [m/s]
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-3
-2
-1
0
1
2
3

Simulation results



QuickTime™ and a decompressor are needed to see this picture.

- Negligible online computation time
- Optimal time (using the MA language): 177 seconds.
- Explicit solution effectiely provides a **feedback** control policy, e.g., providing robustness w.r.t. environmental disturbances.

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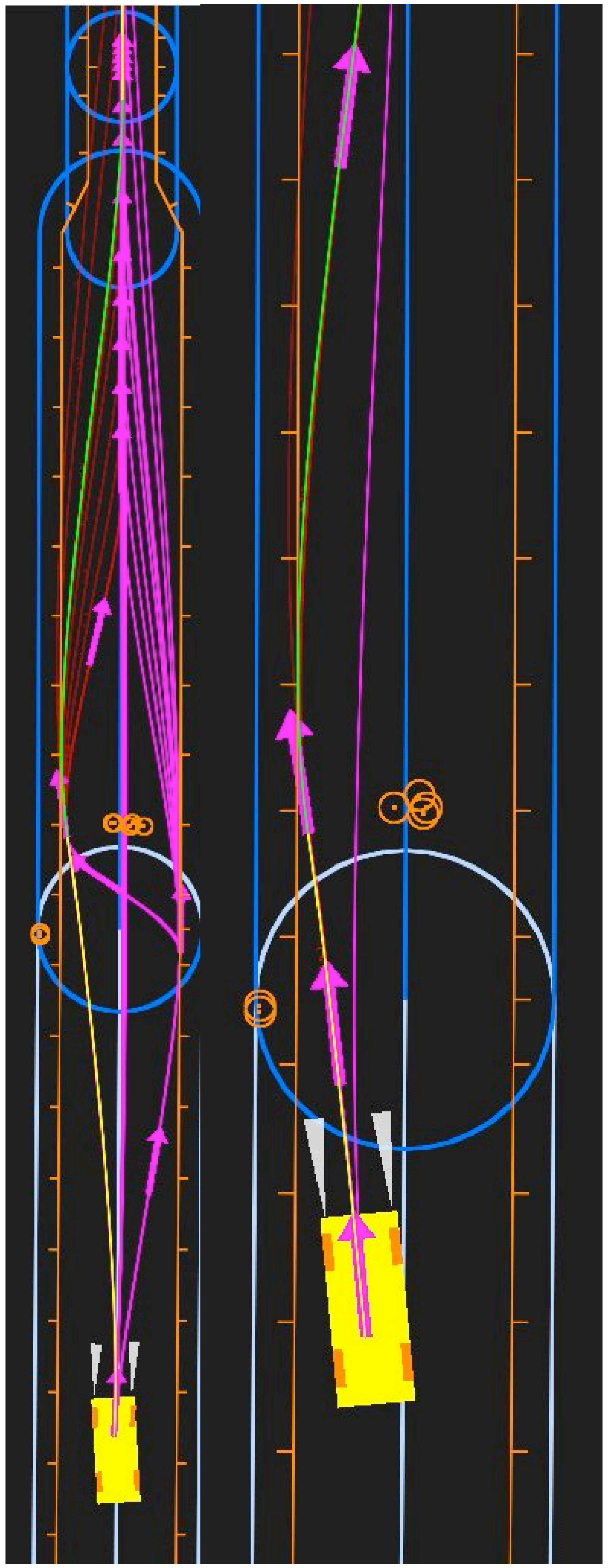
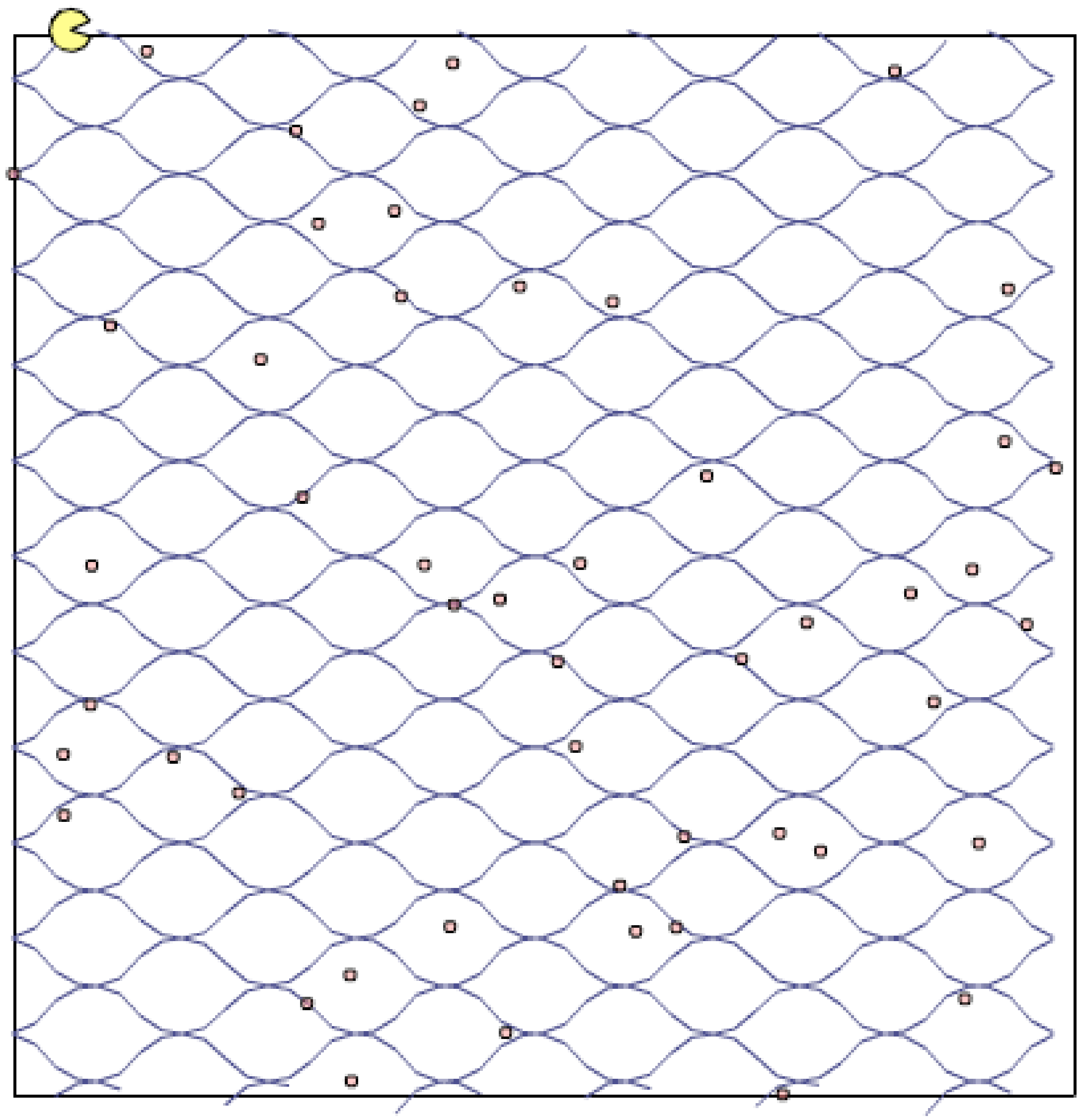
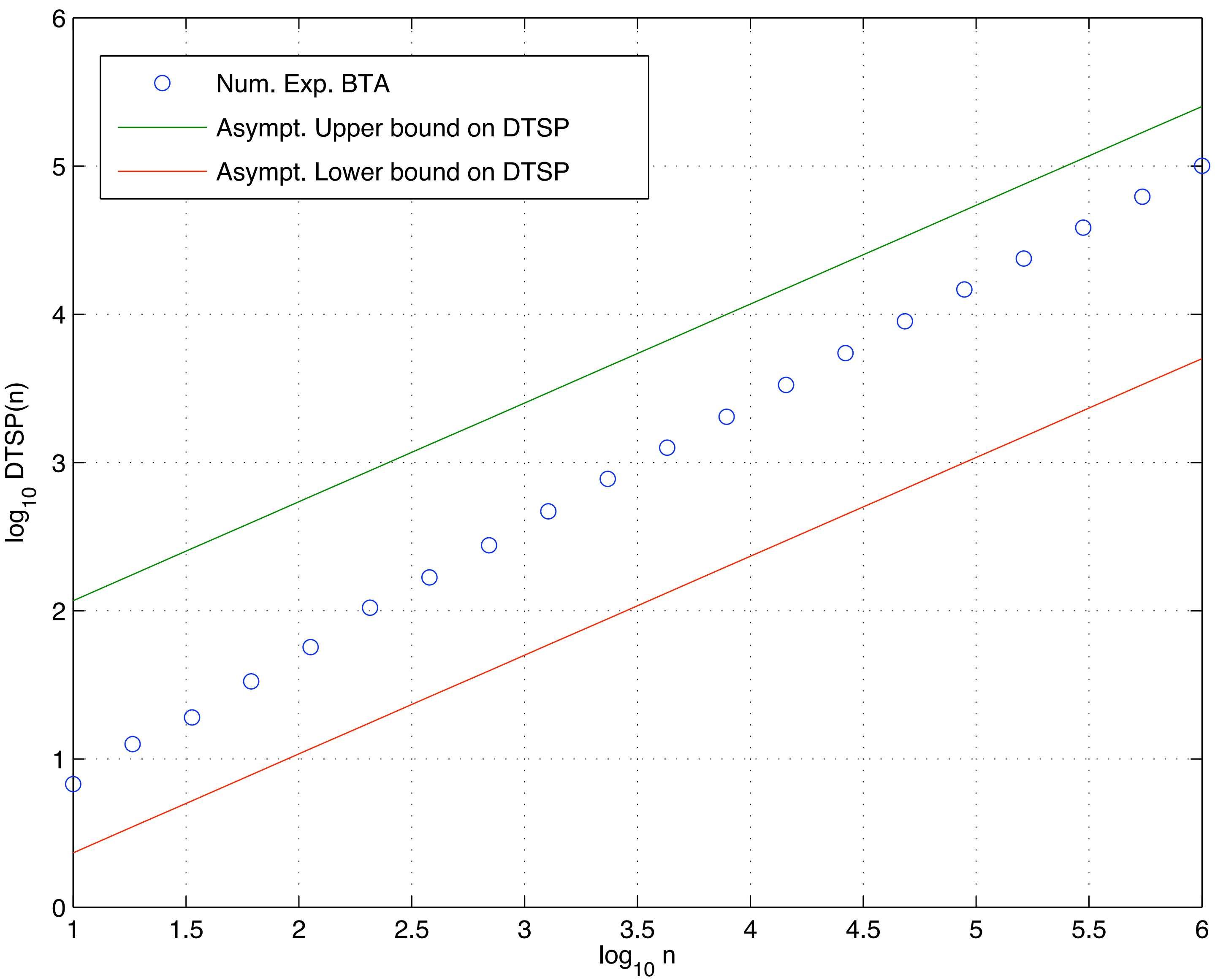
An enabling tool for real-time motion planning

- "Symbolic" trajectory generation compatible with state-of-the-art algorithms for motion planning.
  - Incremental sampling-based search algorithms (RRTs, [LaValle & Kuffner]) implemented successfully (e.g., on the UCLA/Golem group DARPA Grand Challenge vehicle).
- Working with a carefully chosen library of "natural trajectory" isolates motion planning from safety/stability concerns.
- Real-time safety guarantees in uncertain environments.



Numerical Experiment Results





High-Speed Motion Planning on Rough Terrain

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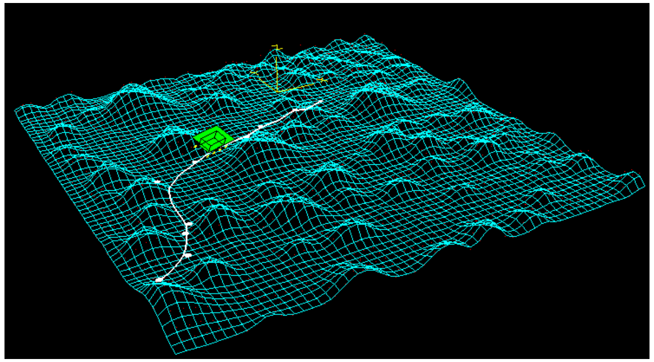


Motivation

- The faster the better
- But how fast?

The Challenges

- **Terrain profile**: must have a good 3D map
- **Obstacles avoidance**: does not apply to rough terrain
- **Vehicle stability**: depends on slope, curvature, and speed
- **Soil properties**: may limit ability to traverse a given terrain segment
- **Computational efficiency:** avoid searching in the state-space
- **Moving obstacles**: avoid other vehicles

This talk

- Describe a unified physics-based planner that addresses
  - Vehicle stability
  - Soil properties
  - Obstacle traversal
  - Online navigation* (Iagnemma)

Vehicle Stability

Stability

Dynamic instability

Static stability

The Problem

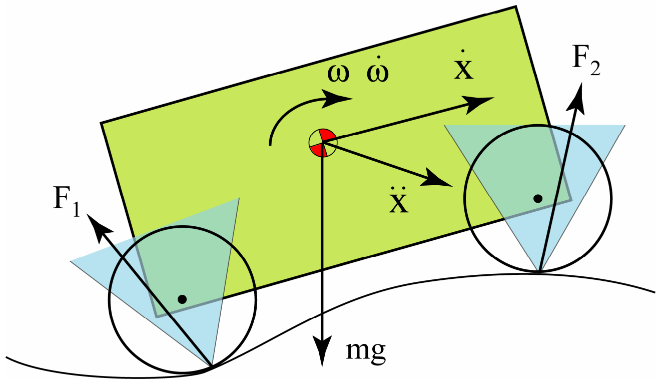
- Where is the vehicle statically unstable?
- At what speed is the vehicle dynamically unstable?

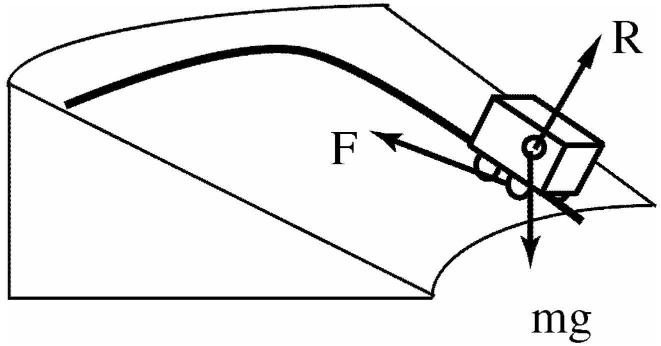
Approach

- Define
  - Static stability: acceleration range at zero speed
  - Dynamic stability: max speed that does not violate dynamics constrains
- Map constraints on ground forces to constraints on speed and acceleration
- Determine static and dynamic stability margins from attainable speeds and accelerations

Treated so far

- Suspended point mass
- Planar rigid body

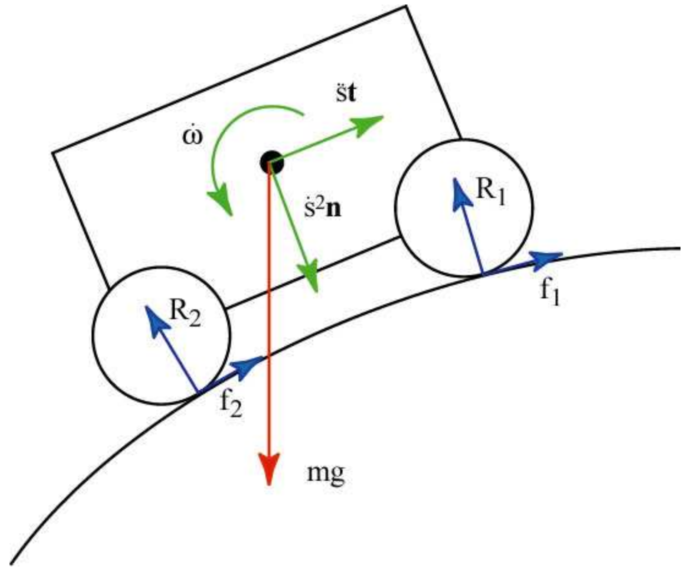




Planar Vehicle Model

- A planar all wheel drive
- 3 DOF (x,y,θ)
- 2 ground forces (4 components)
- Equations of motion:

$$F_1 + F_2 = m(\ddot{x} - g)$$
$$r_1 \times F_1 + r_2 \times F_2 = I\dot{\omega}$$

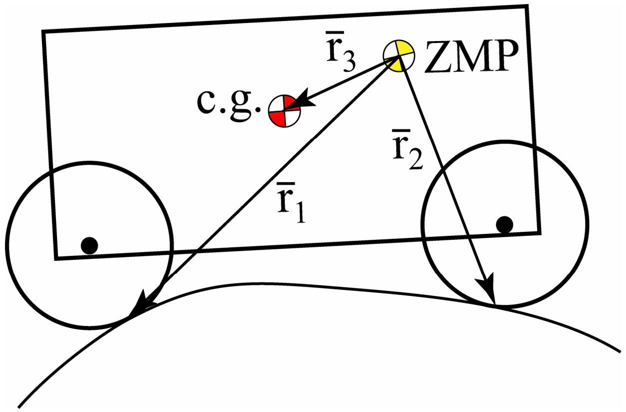


$$F_1 = f_1 + R_1$$
$$F_2 = f_2 + R_2$$

Moment Equation

Moment equation becomes an equality constraint

$$\boxed{\bar{r}_1 \times F_1 + \bar{r}_2 \times F_2 + \bar{r}_3 \times mg \;\; = 0}$$



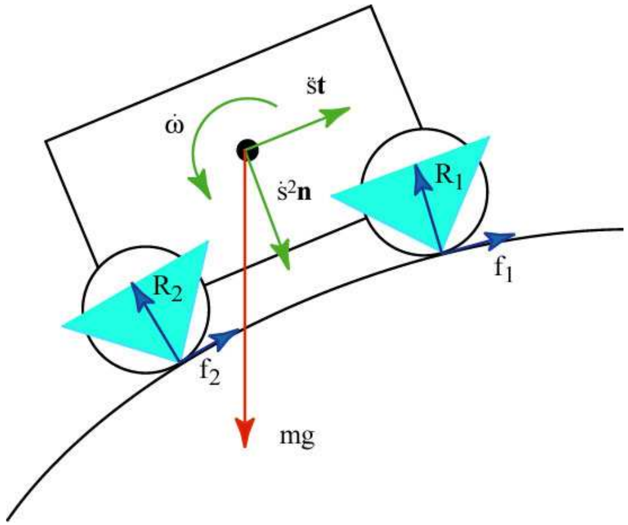
- External forces must produce a zero moment around ZMP
- ZMP reflects body inertia and path curvature

Dynamic Constraints

- 7 constraints:
  - 6 force inequality constraints
  - 1 moment equality constraint:

$$f_1 < \mu R_1$$
$$f_1 > -\mu R_1$$
$$f_2 < \mu R_2$$
$$f_2 > -\mu R_2$$
$$R_1 > 0$$
$$R_2 > 0$$

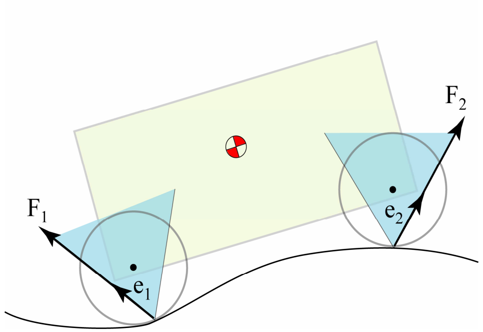
$$\bar{r}_1 \times F_1 + \bar{r}_2 \times F_2 + \bar{r}_3 \times mg \quad = 0$$



Constraints on Speed and Acceleration I

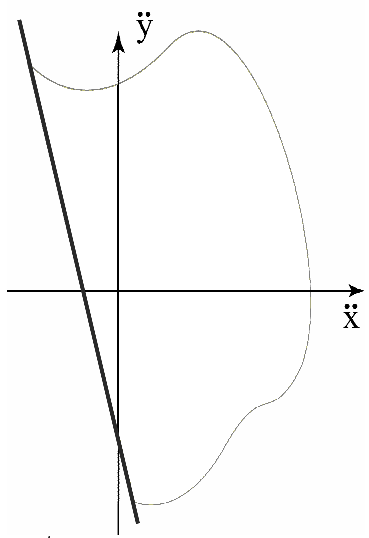
- Pick any 2 force equality constraints

$$F_1 = \mathrm{f}_1 \mathbf{e}_1$$
$$F_2 = \mathrm{f}_2 \mathbf{e}_2$$



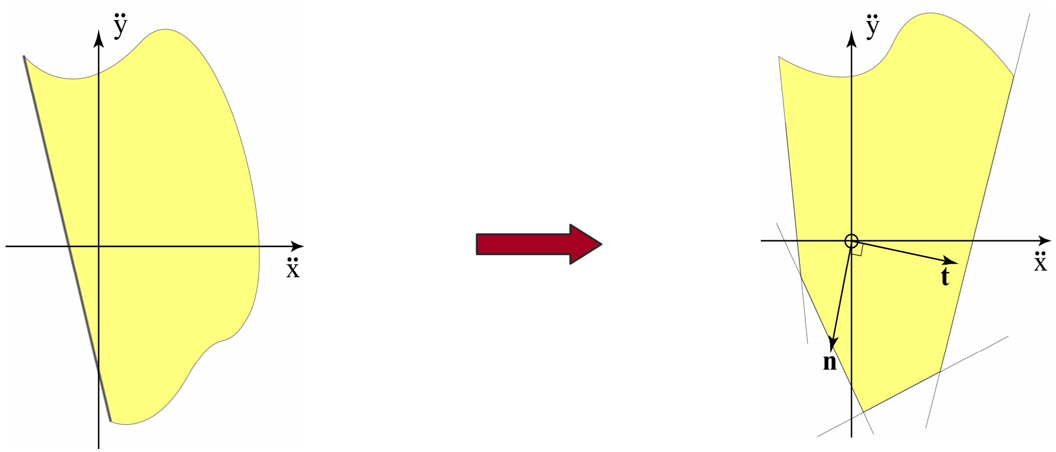
- Express forces in terms of cg acceleration
- Substitute in moment equation
- Obtain a line in $\ddot{x}-\ddot{y}$ plane

$$\boxed{a\ddot{x} + b\ddot{y} + c = 0}$$



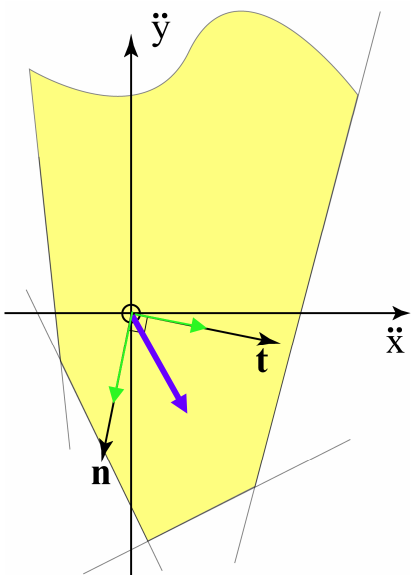
Constraints on Speed and Acceleration II

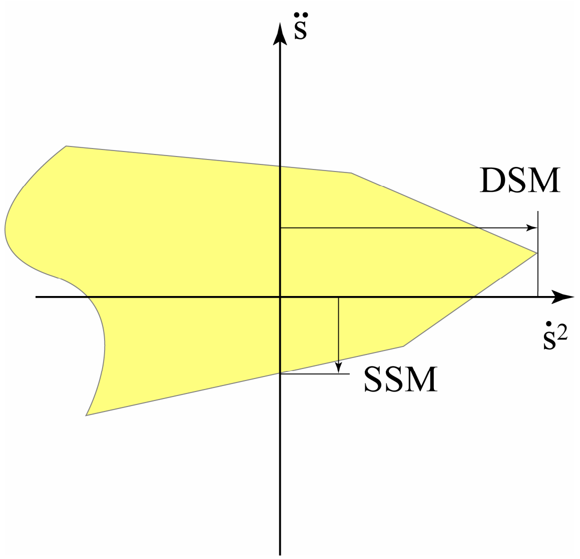
- *Inequality* part of constraints maps to a half plane in $\ddot{x}-\ddot{y}$ plane
- Intersecting all half planes produces the set of admissible accelerations



Map cg acceleration to path coordinates

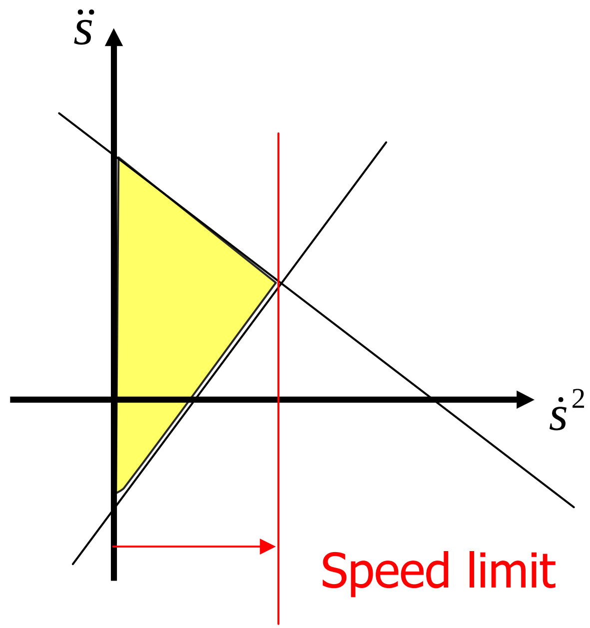
$$\begin{bmatrix} \dot{s}^2 \\ \ddot{s} \end{bmatrix} = K^{-1} \begin{bmatrix} \ddot{x} \\ \ddot{y} \end{bmatrix}$$





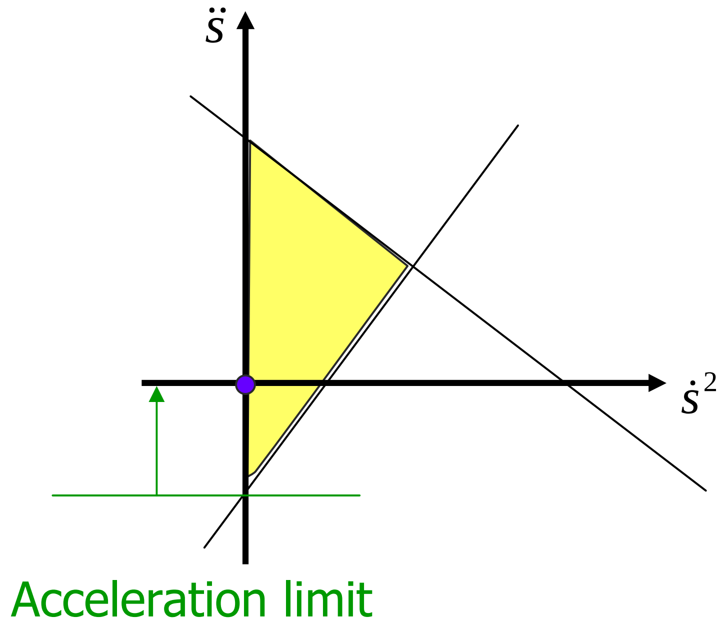
Dynamic Stability Margin

- Maximum speed: reflects curvature, slope and friction constraints



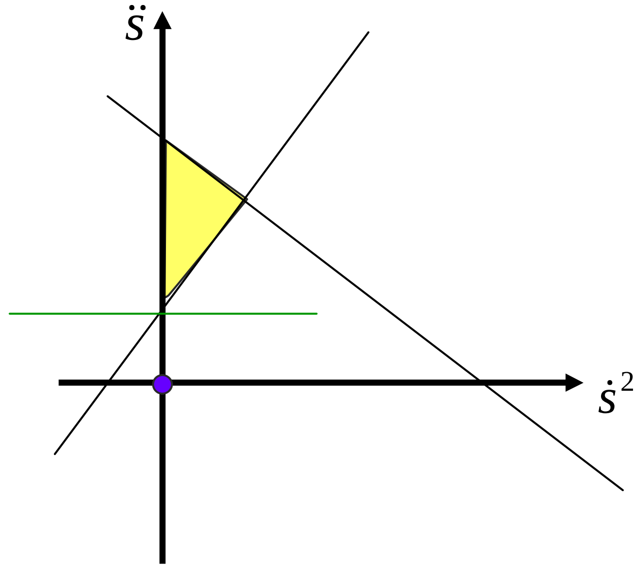
Static Stability Margins

- Maximum symmetric acceleration range at zero speed: reflects slope and friction constraints

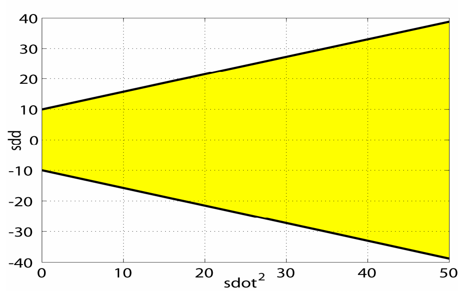


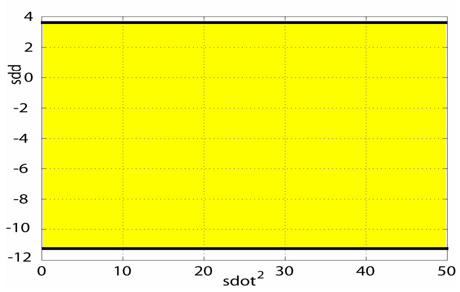
Statically Unstable

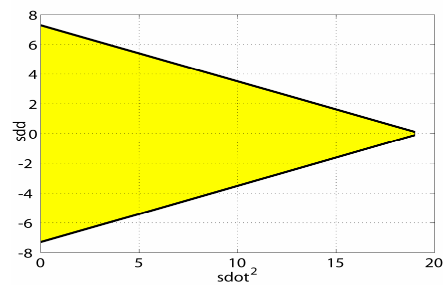
- Vehicle cannot sustain its position at zero speed



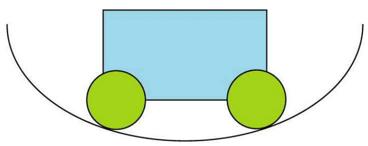
Example



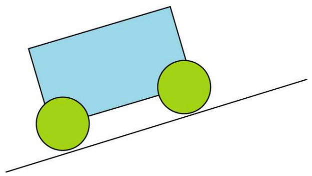




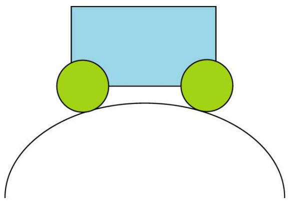
Concave



Flat incline

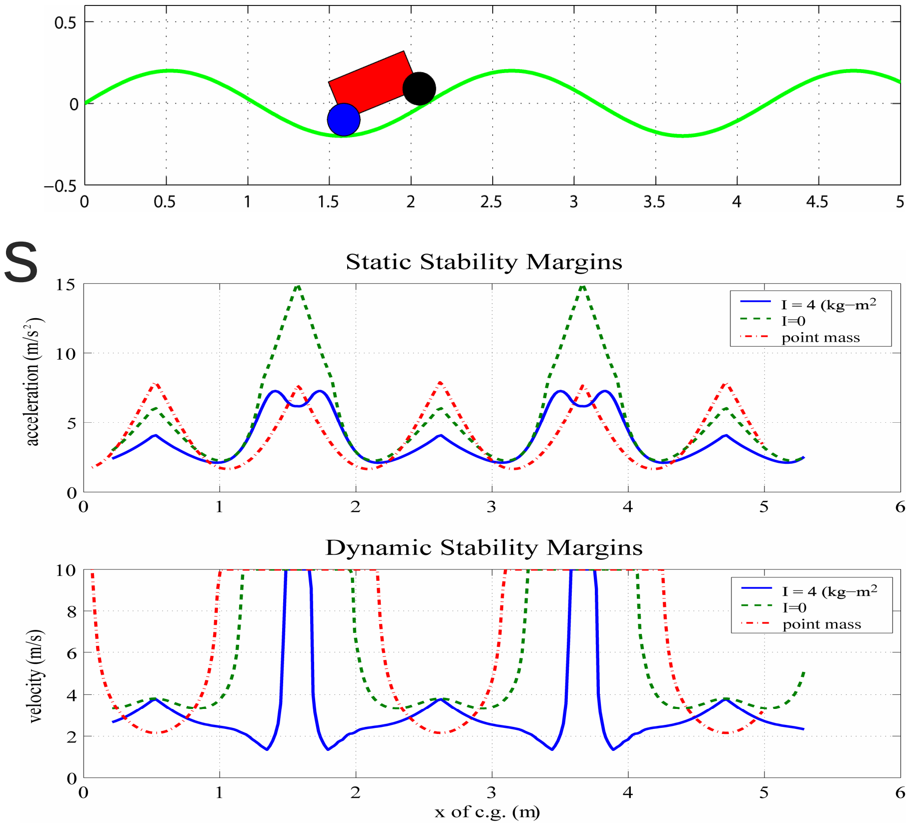


Convex



Example: Sinusoidal Path, all wheel drive

- Rigid body
- Suspended point mass
- Point mass



Soil Properties

The Problem

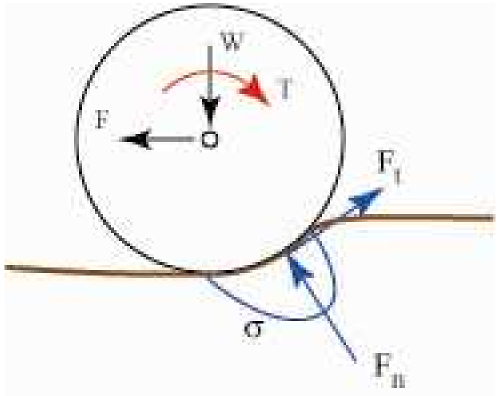
- At what speed can, or should, the vehicle move on sandy soil?
- What is the steepest slope it can climb?

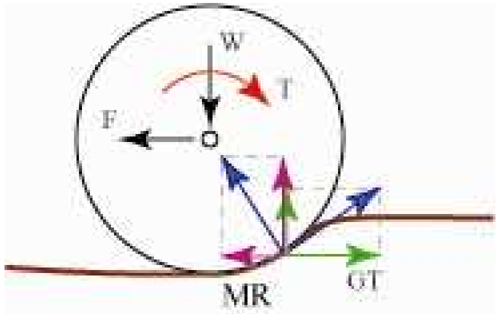
Approach

- Incorporate wheel/ground model into the stability analysis
- Brixius model:

  Brixius, W. W, 1987. Traction prediction equations for bias ply tires. ASAE paper no. 87-1622, ASAE, St. Joseph, MI 49085.
- Focus on a longitudinal model

Ground forces





- Net traction: $$NT = GT - MR$$
- Net braking: $$NB = GT + MR$$

Brixius Model

- Cone index *CI*
- Mobility number *Bn*

$$B_n = \frac{CI \cdot b \cdot d}{W}\left(\frac{1+5\frac{\delta}{h}}{1+3\frac{b}{d}}\right)$$

- Slip ratio *s*

$$s = 1 - \frac{V_x}{r_0 \omega}$$

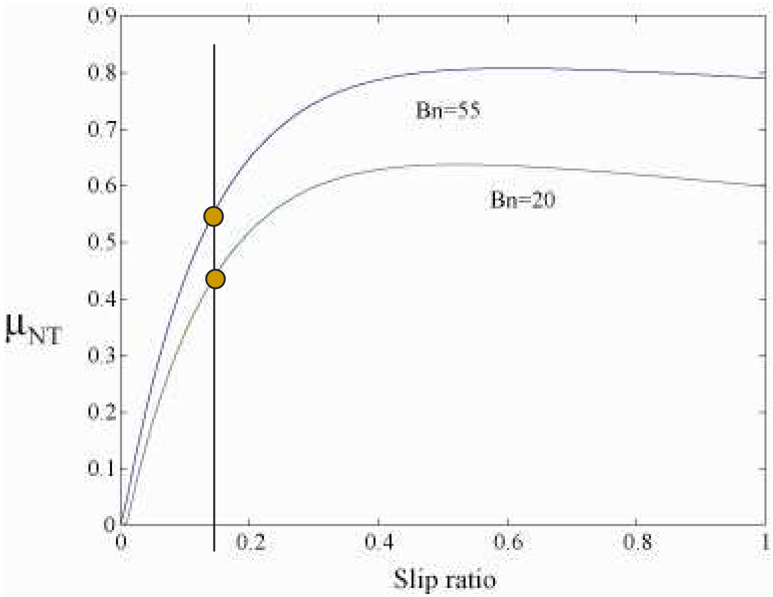
- Net traction

$$NT = 0.88W(1-e^{-0.1B_n})(1-e^{-7.5s}) - \left(\frac{1}{B_n} + \frac{0.5s}{\sqrt{B_n}}\right)$$

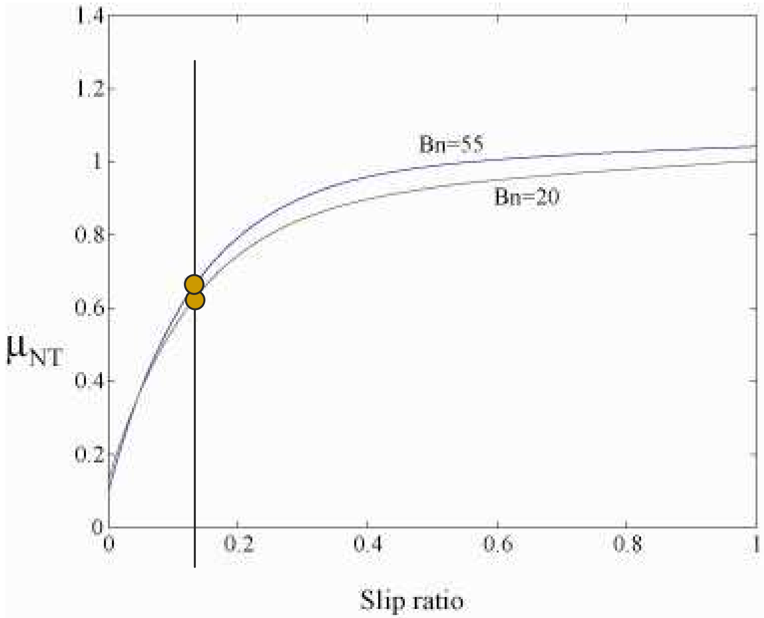
- Net braking

$$NB = -0.88W(1-e^{-0.1B_n})(1-e^{7.5s}) - \left(\frac{1}{B_n} - \frac{0.5s}{\sqrt{B_n}}\right)$$

Net Traction/Braking Coefficient

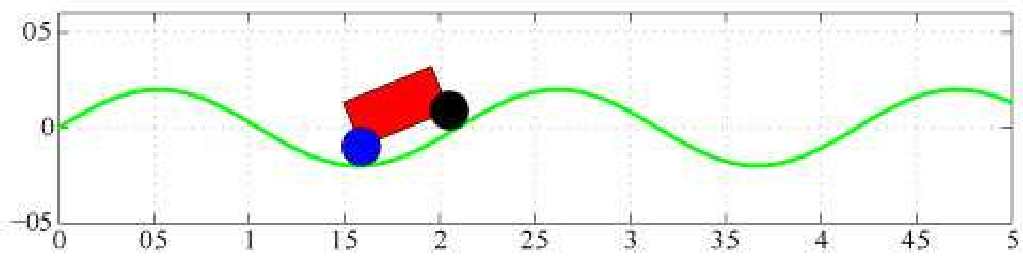


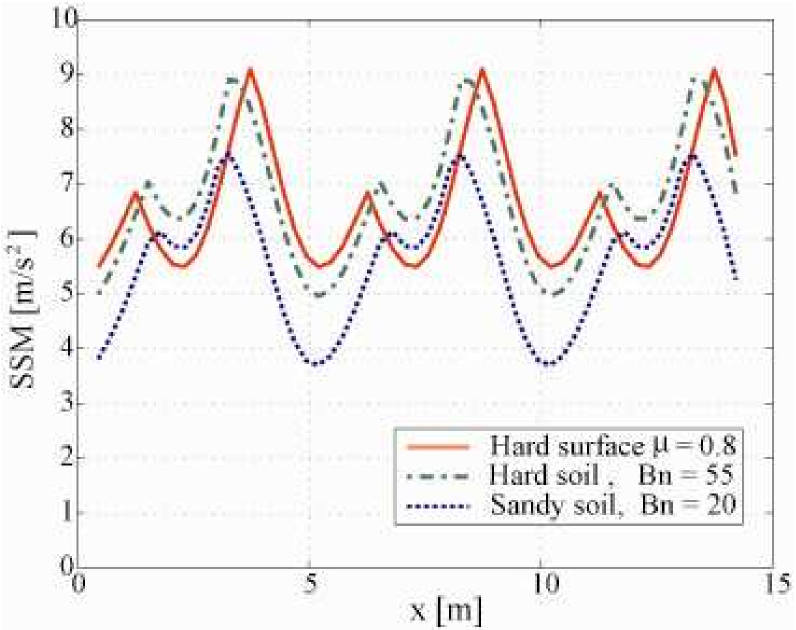
Net Traction Coefficient

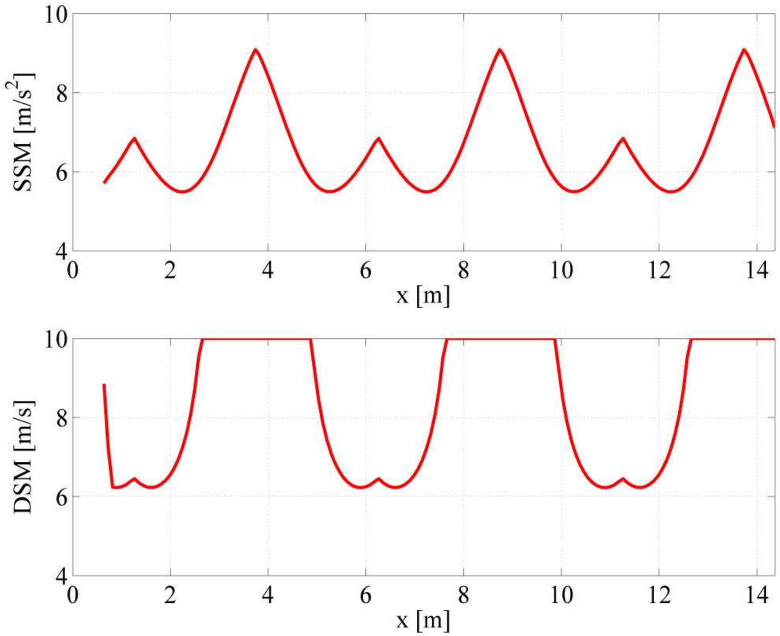


Net Braking Coefficient

Example: effect of soil properties







Obstacle Traversal

The Problem

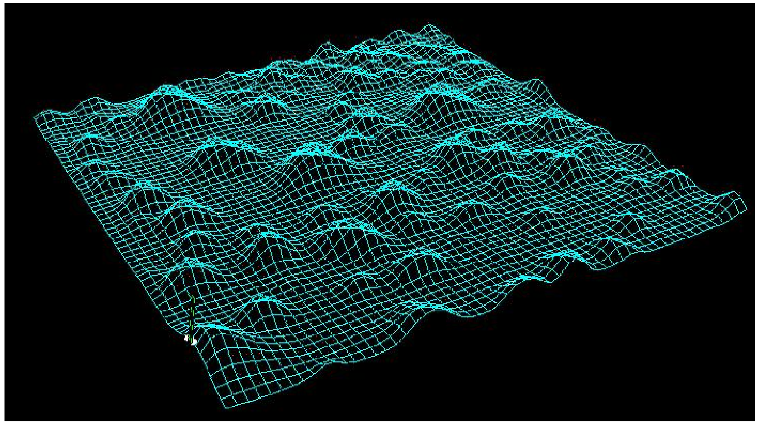
- Avoid or climb?
- Not just a kinematic problem

Approach

- Model terrain and obstacles by a smooth representation
- Introduce a continuous traversability measure based on dynamic stability
- Maximize traversability
- Minimize motion time

Terrain Representation

- Represent surface by a smooth B-patch
- Embed obstacles in the B-patch



Traversibility Measure

- Traversability = dynamic stability margin

$$\dot{s}_m(s)$$

- Cost for a path segment

$$C = \frac{ds}{\dot{s}_m}$$

Motion Planning

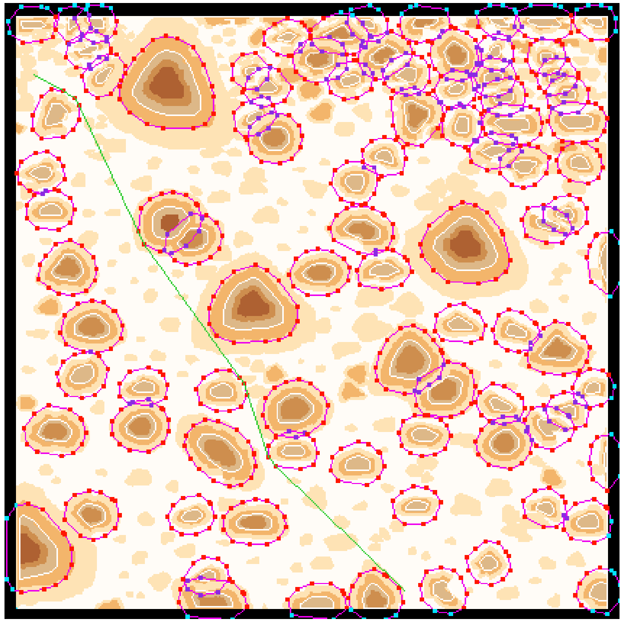
- Represent terrain by a 2D grid
- Compute $\frac{ds}{\dot{s}_m}$ for each edge
- Search for a set of shortest traversable paths

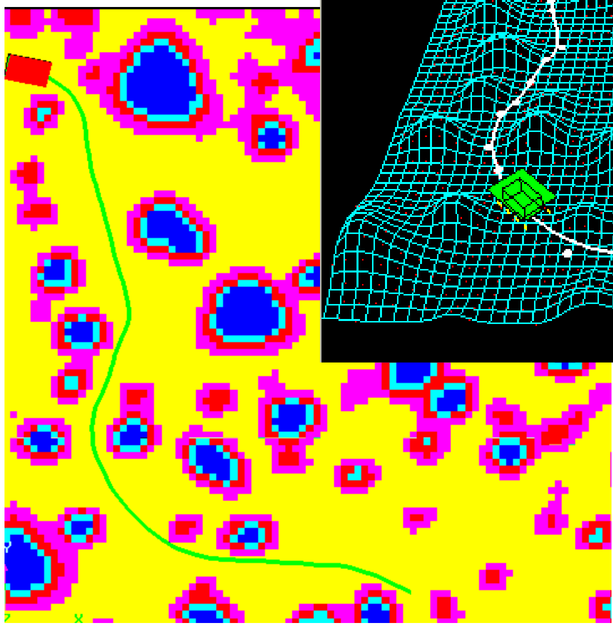
$$\min \int \frac{ds}{\dot{s}_m}$$

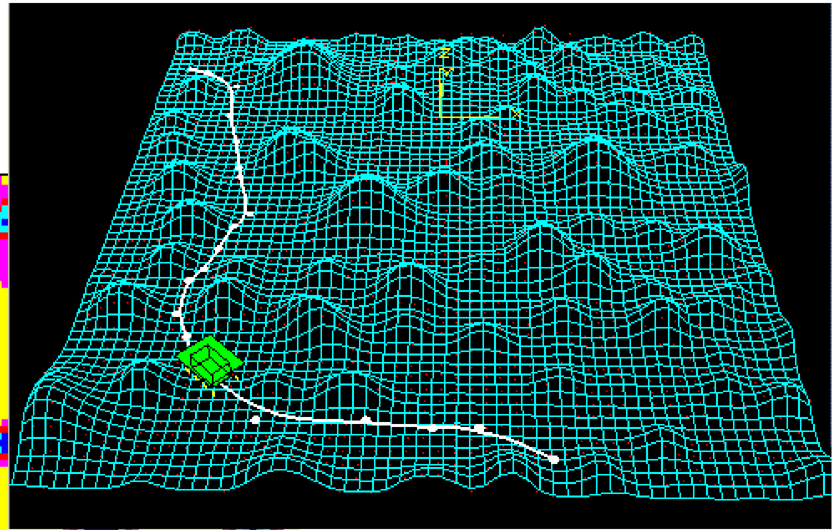
- Traversable path is the initial guess to a local min time optimization

Example

Best traversable Path

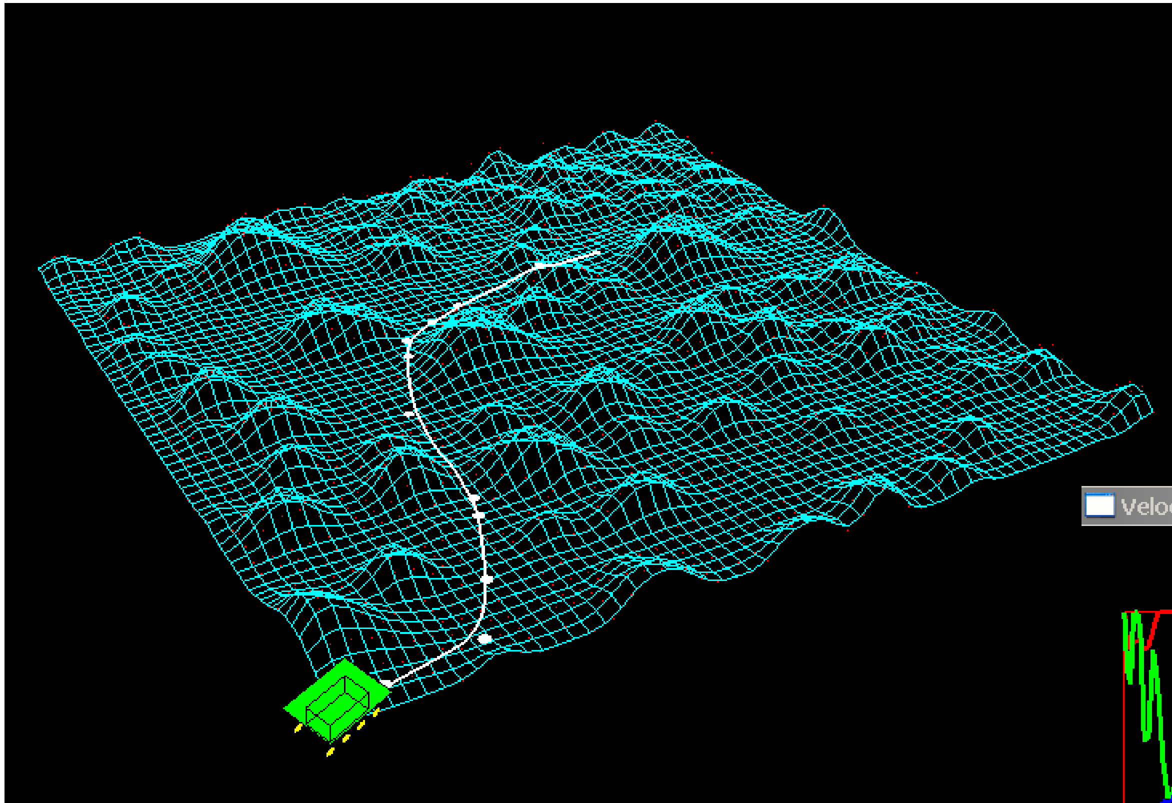


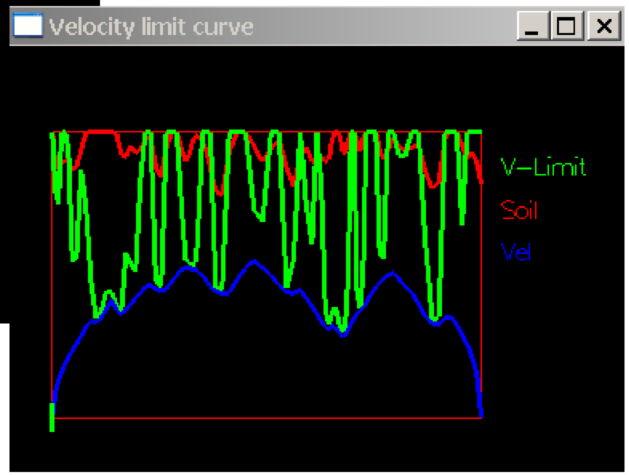




Shortest Path
(Laubach, JPL)

Demo





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Shiller, Z., Gwo R.Y., "Dynamic Motion Planning of Autonomous Vehicles," *IEEE Journal of Robotics and Automation*, Vol. 7, No. 2, April 1991, pp. 241-249.

Shiller, Z., Sundar, S., "Emergency Maneuvers of AHS Vehicles", SAE 1995 Transactions, *Journal of Passenger Cars*, Section 6, Vol. 104, Paper 951893, pp. 2633-2643.

Shiller, Z., Sundar S., "Emergency lane-change maneuvers of autonomous vehicles," *ASME Journal of Dynamic Systems, Measurement and Control,* Vol. 120, No. 1, March 1998, pp. 37-44.

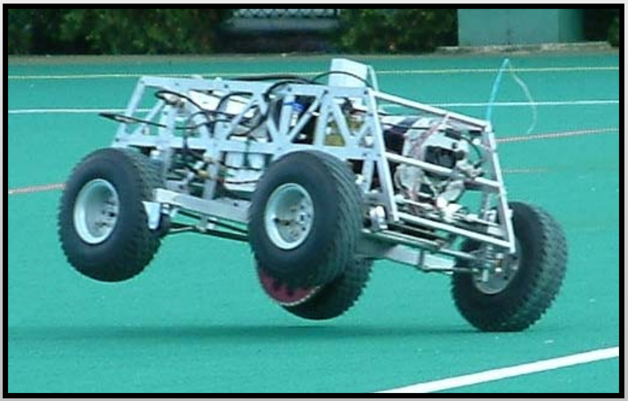
Shiller, Z., "Obstacle Traversal for Space Exploration," ICRA 2000, San Francisco.

Moshe P. Mann and Zvi Shiller: " Dynamic Stability of Off-Road Vehicles: A Geometric Approach," ICRA 2006, Orlando, pp. 3705-3710.

Hazard Avoidance for High-Speed Unmanned Ground Vehicles in Rough-Terrain

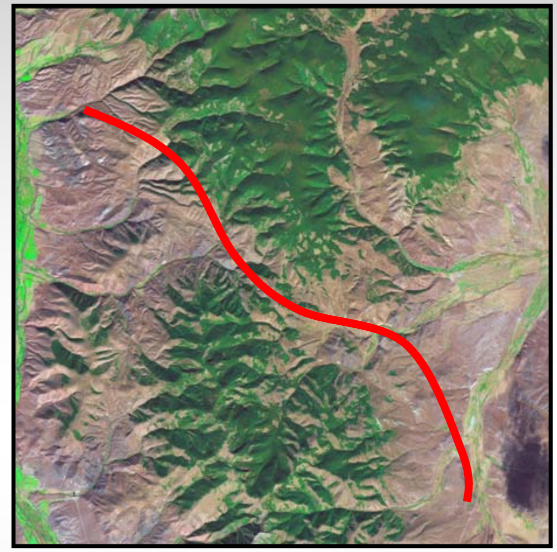
Dr. Matthew Spenko

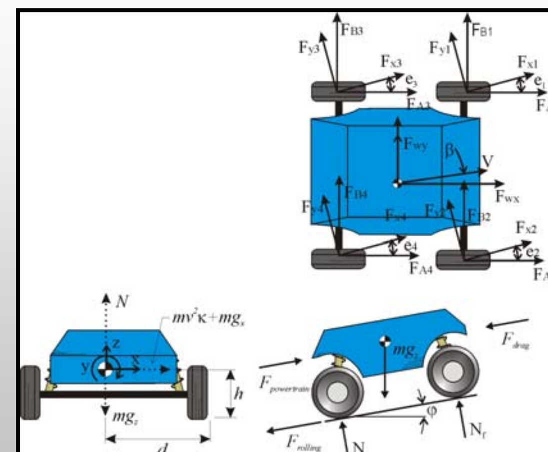
October 5, 2006



Assumed Scenario

- Pre-planned path
- Onboard sensors
  - Range sensor
  - Inertial navigation sensor
  - GPS
- Vehicle speed (and terrain) can cause slip, ballistic motion, and roll over
- *A priori* knowledge
  - Vehicle parameters
    - Inertia, stiffness, mass
  - Topographical map
  - Large-scale soil type estimate
  - Terrain roughness estimate

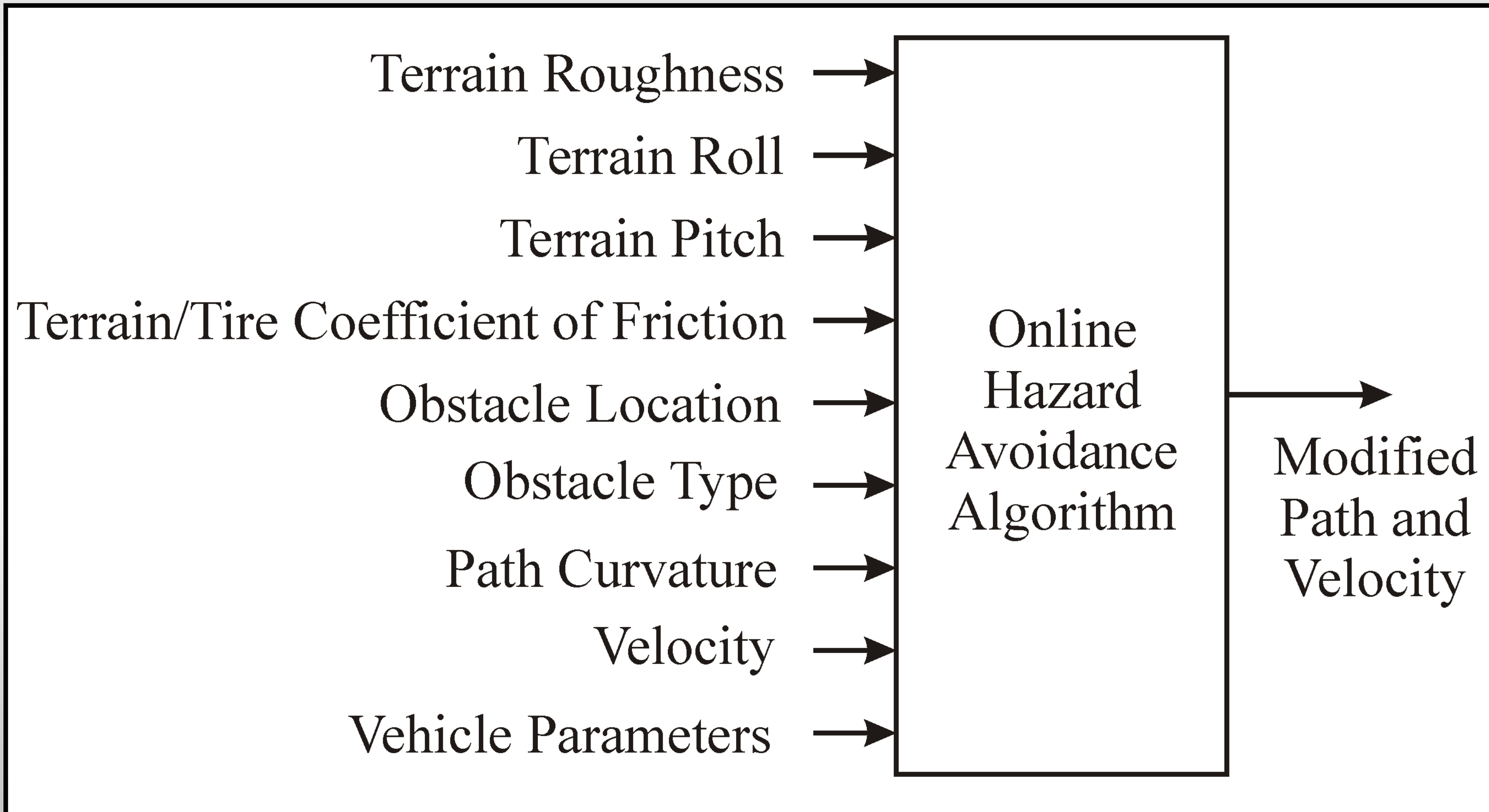




Research Challenges

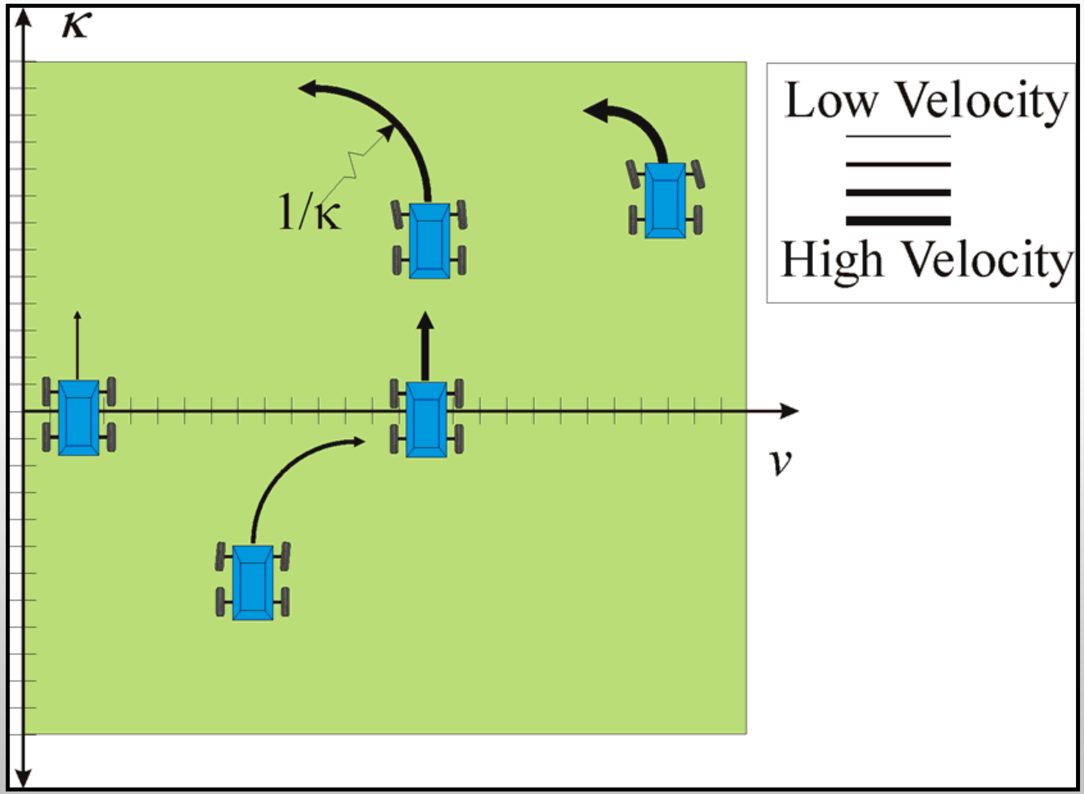
- Dynamically feasible
- Computationally efficient
- Vehicle/terrain interaction effects
- Uncertainty in the terrain profile
- Applicable in highly unstructured environments
- Hazards are not solely binary manner
- Consider vehicle characteristics

Proposed Solution



The Trajectory Space

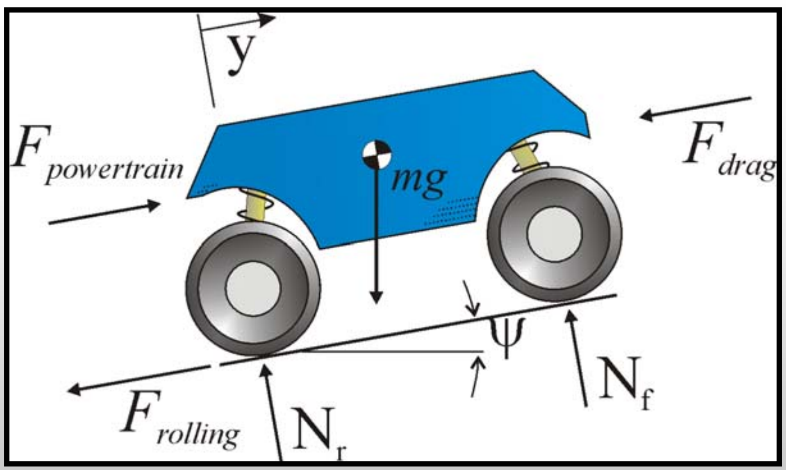
- The trajectory space is a compact representation of a vehicle's performance limits

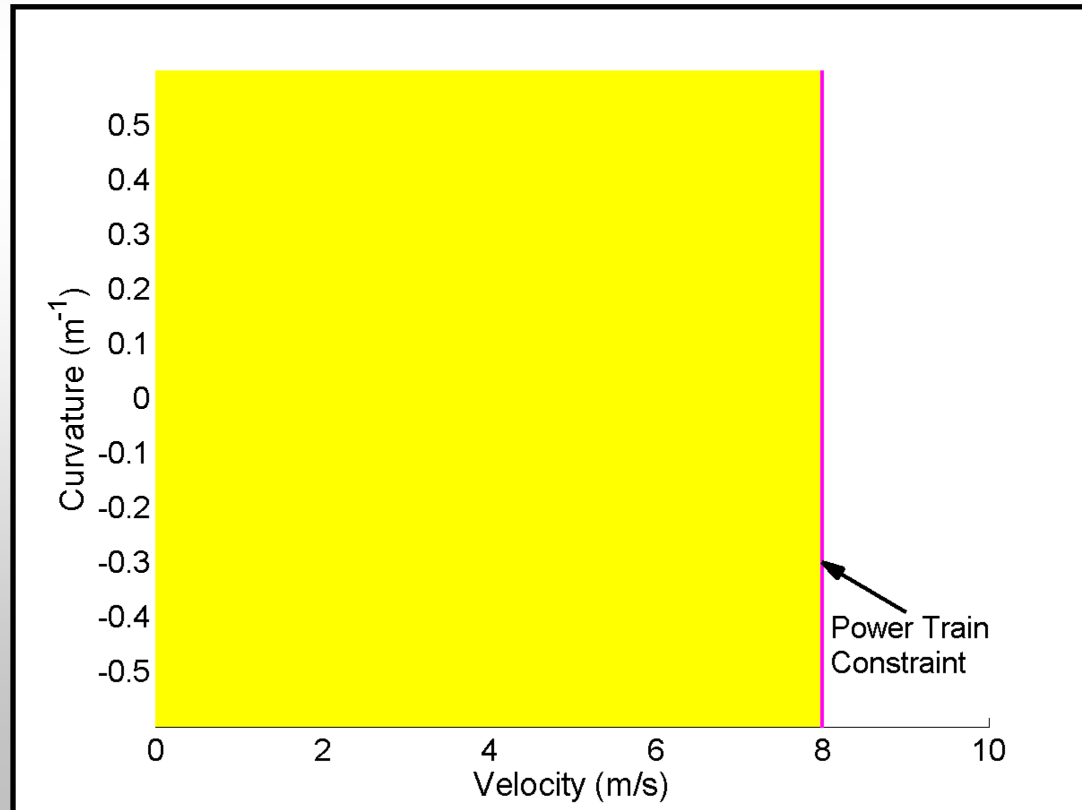


Dynamic Constraints

- Power train constraints
  - Engine
  - Terrain pitch
  - Aerodynamic drag
  - Rolling resistance

$$v_{\max} = \sqrt{\frac{2(T(v)G - rC_{rr}mg\cos\psi - rmg\sin\psi)}{rA_r\rho C_d}}$$

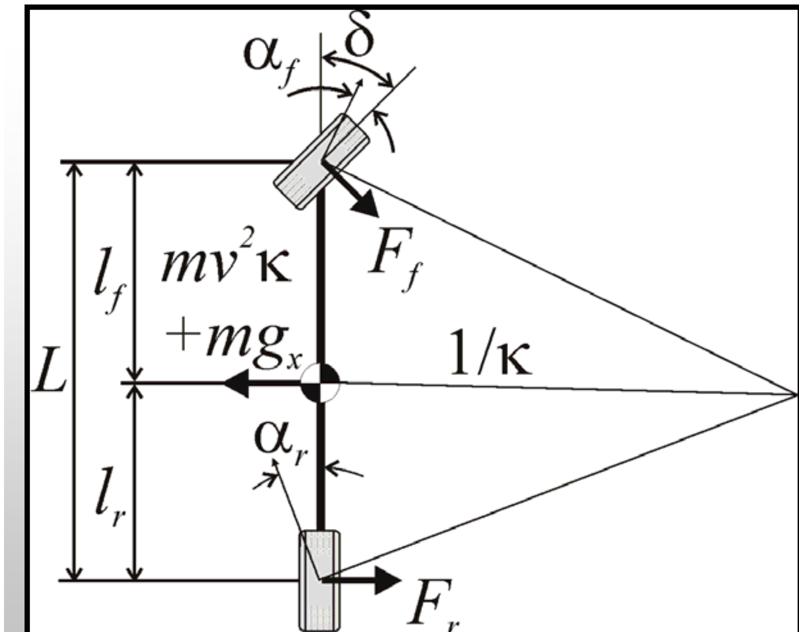


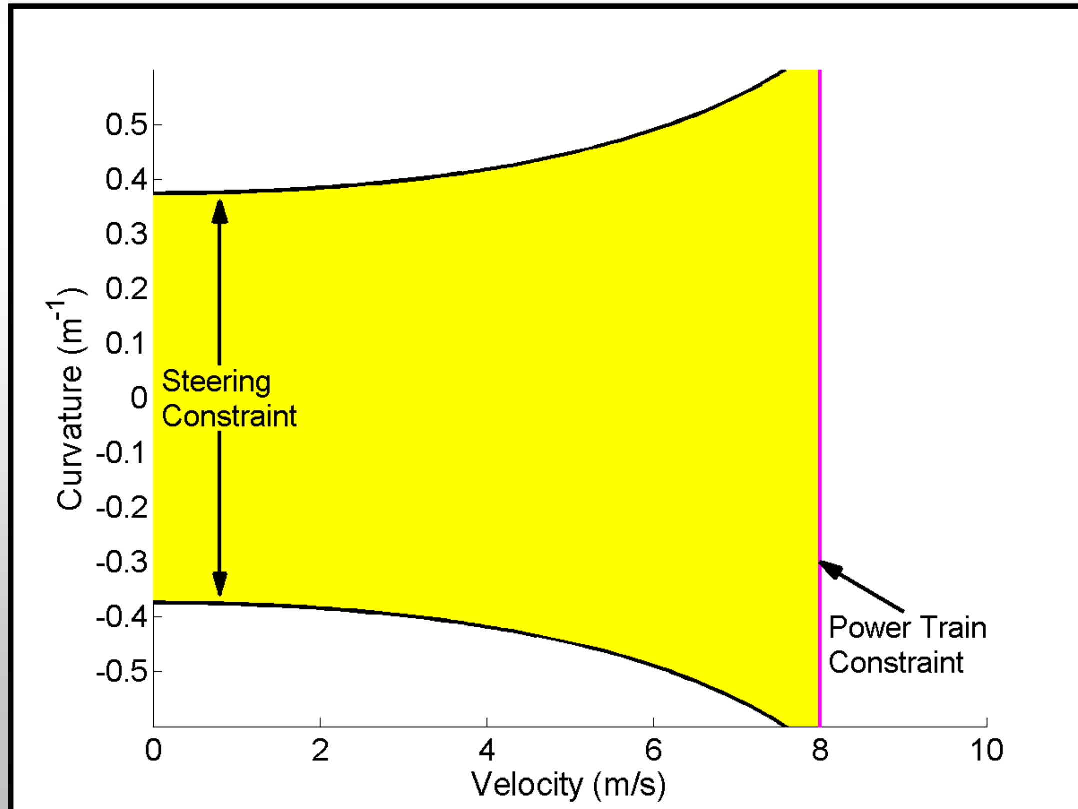


Dynamic Constraints

- Steering constraints
  - Tire cornering stiffness
  - Center of mass location
  - Wheelbase
  - Steering angle

$$\kappa_{steering}^{\max,\min} = \frac{C_k L \tan\delta_{\max} \pm m g_x \left(l_f - l_r\right)}{\left(C_k L^2 + m v^2 \left(l_r - l_f\right)\right)}$$

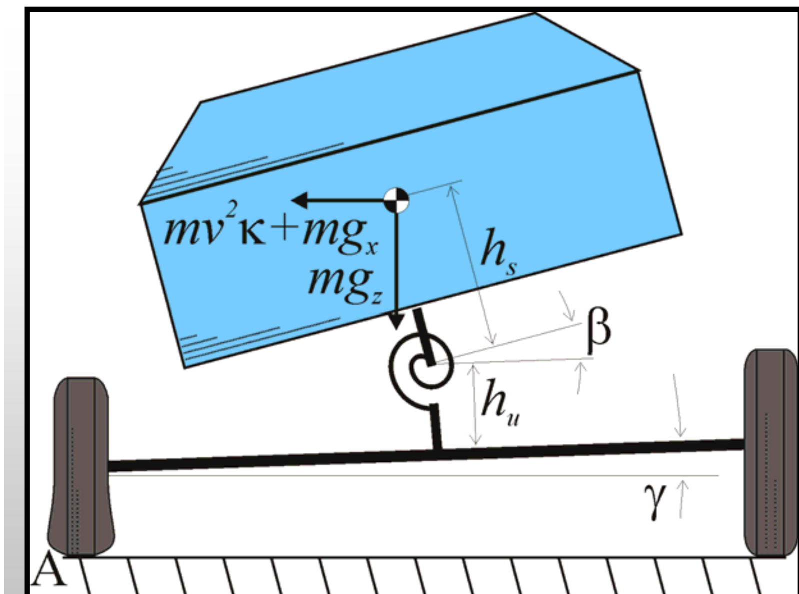


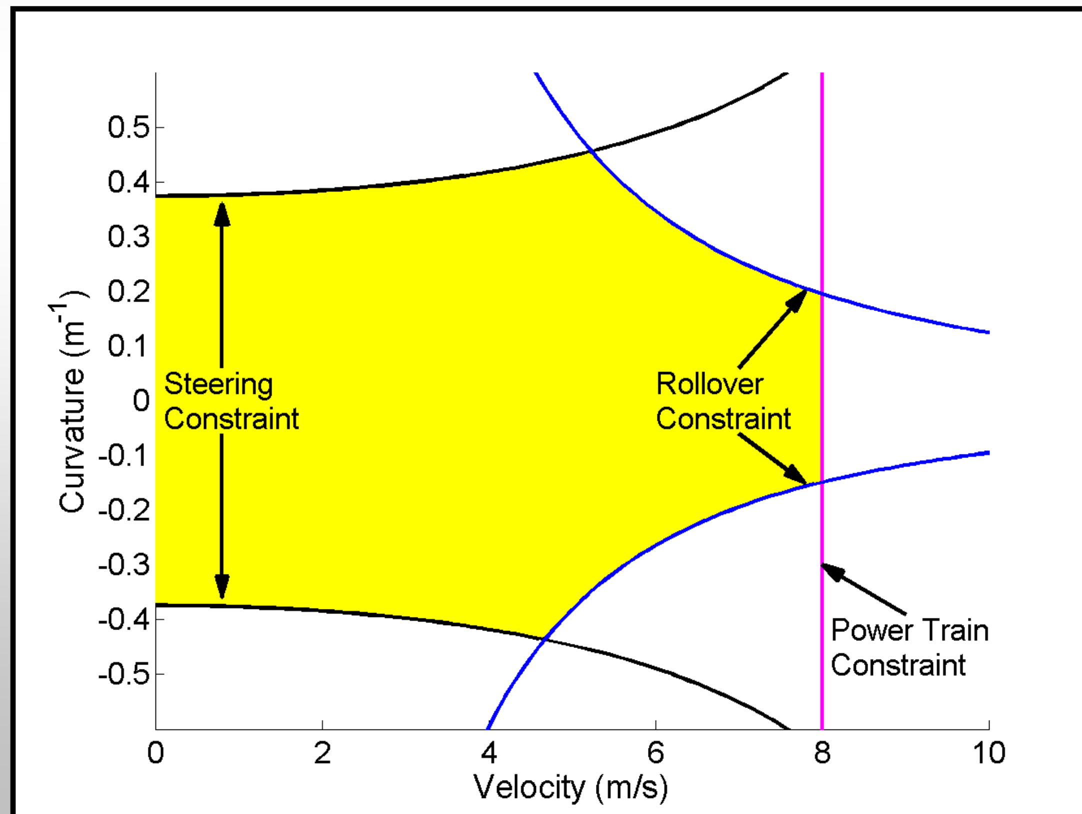


Dynamic Constraints

- Rollover constraints
  - Vehicle properties
  - Track width
  - Sprung/ Unsprung mass height
  - Suspension properties

$$\kappa_{rollover}^{\max,\min} = \frac{(d - h\gamma - h_s\beta)g_z \pm (h + d\gamma)g_x}{(h + d\gamma)v^2}$$

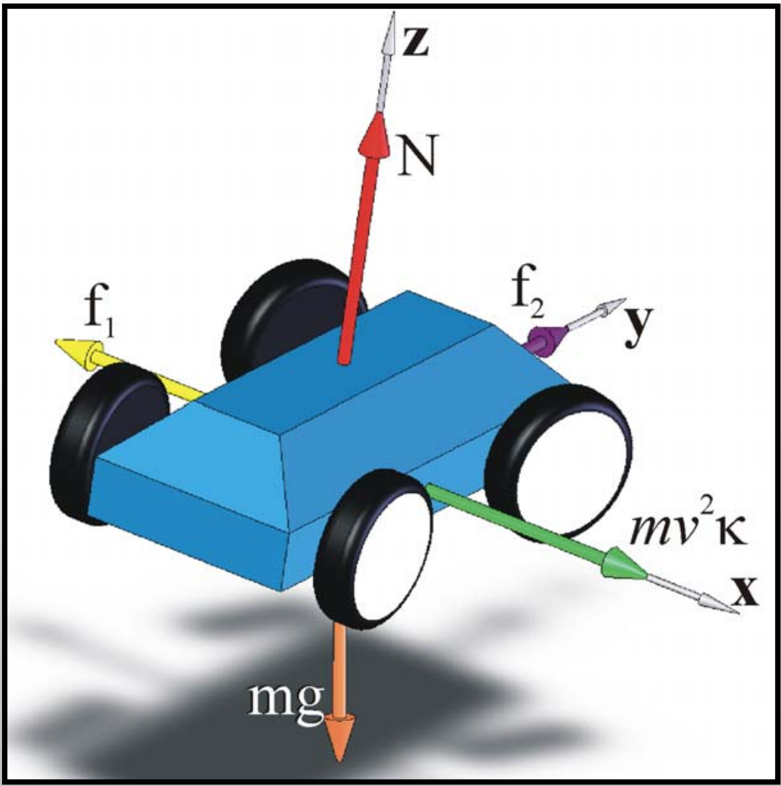


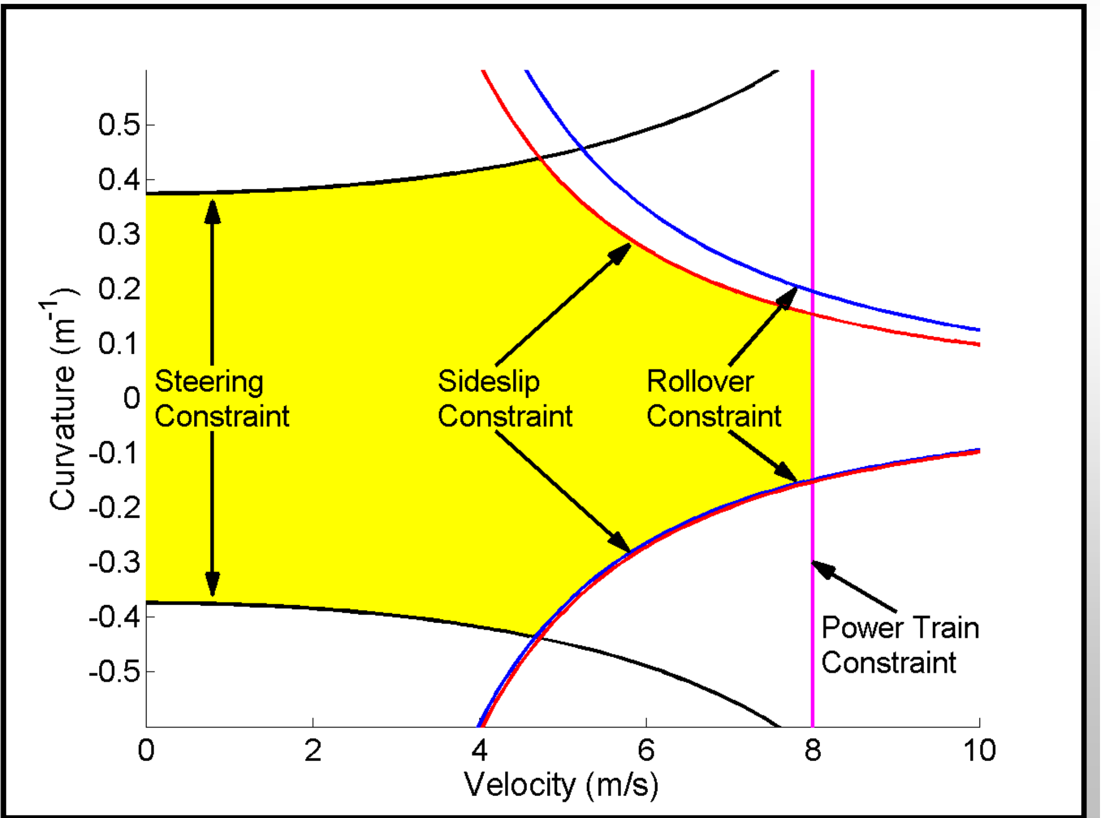


Dynamic Constraints

- Sideslip constraints
  - Terrain inclination
  - Traction coefficient

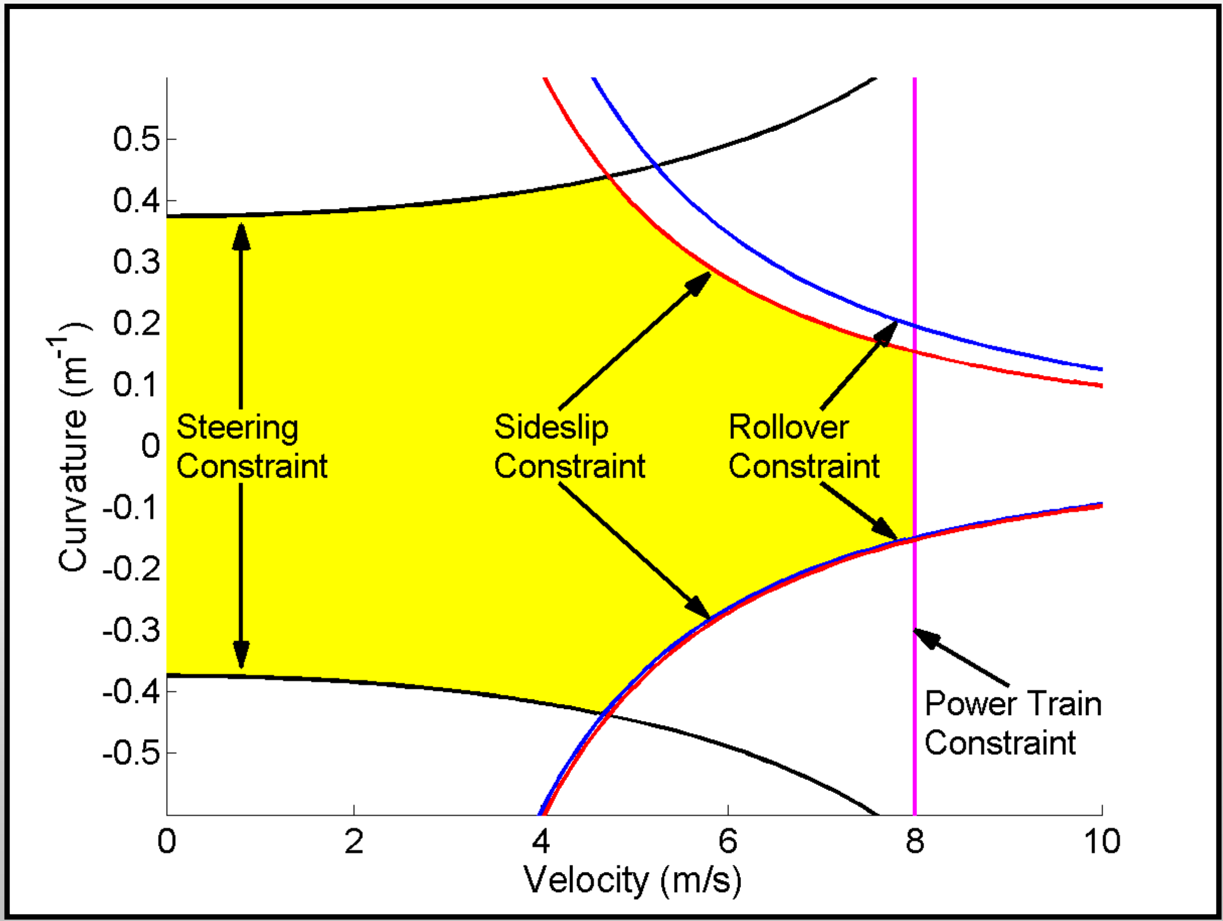
$$\kappa_{slip}^{\min,\max} = \frac{-g_x \pm \mu g_z}{v^2}$$



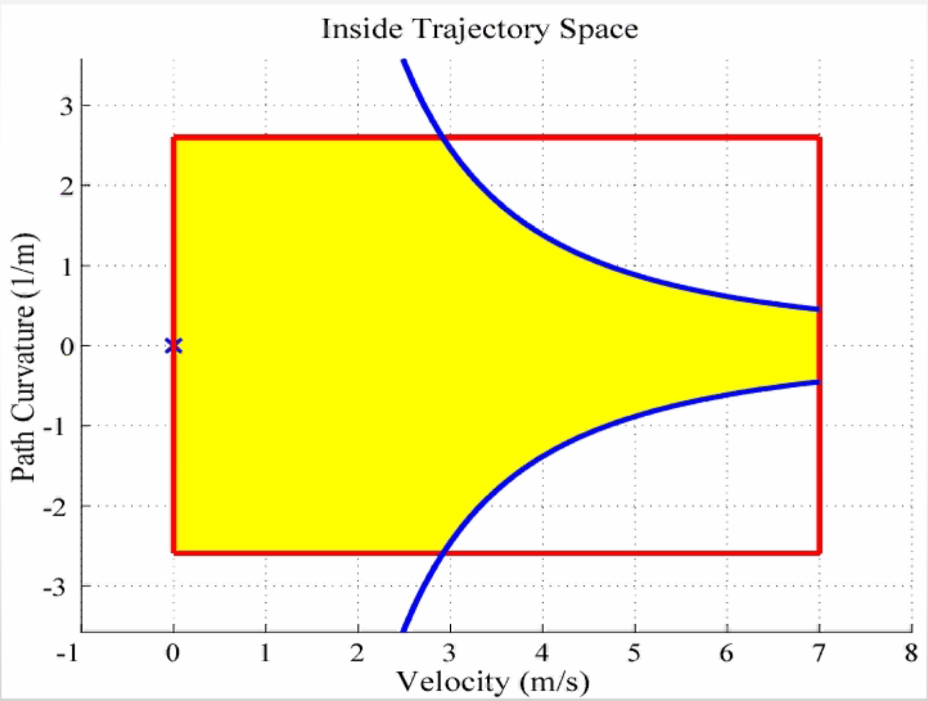


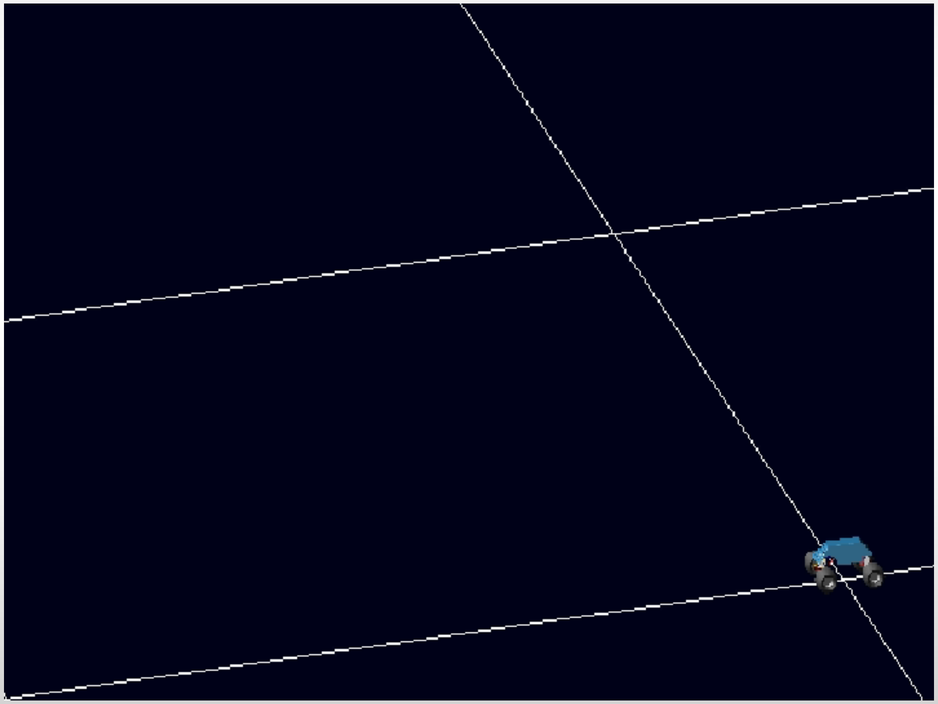
Dynamic Trajectory Space, Γ

- The set of velocity and curvature pairs that are dynamically admissible on a given terrain patch

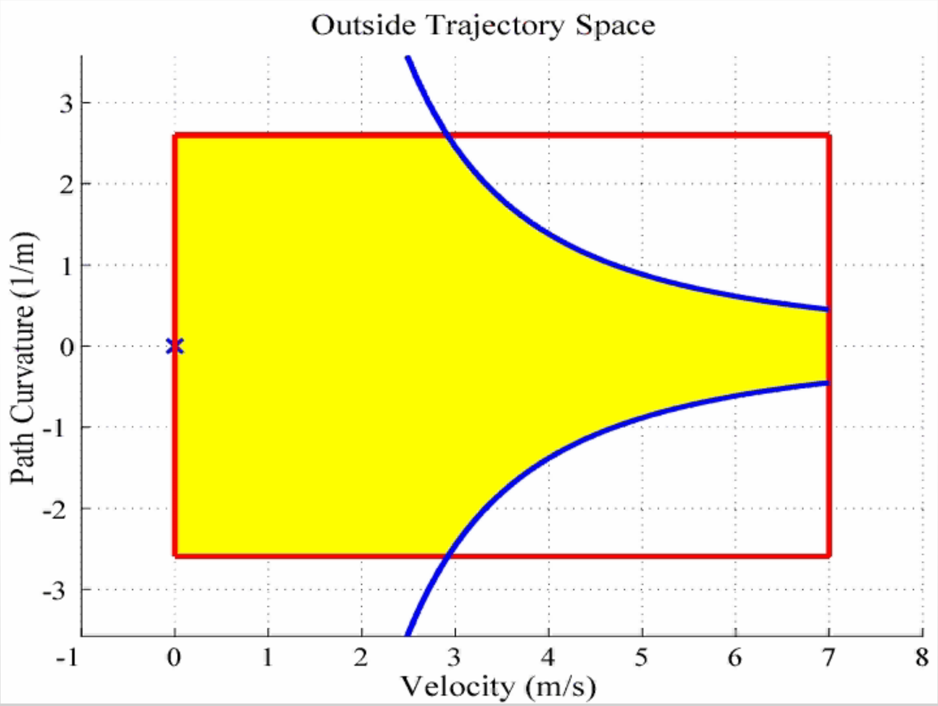


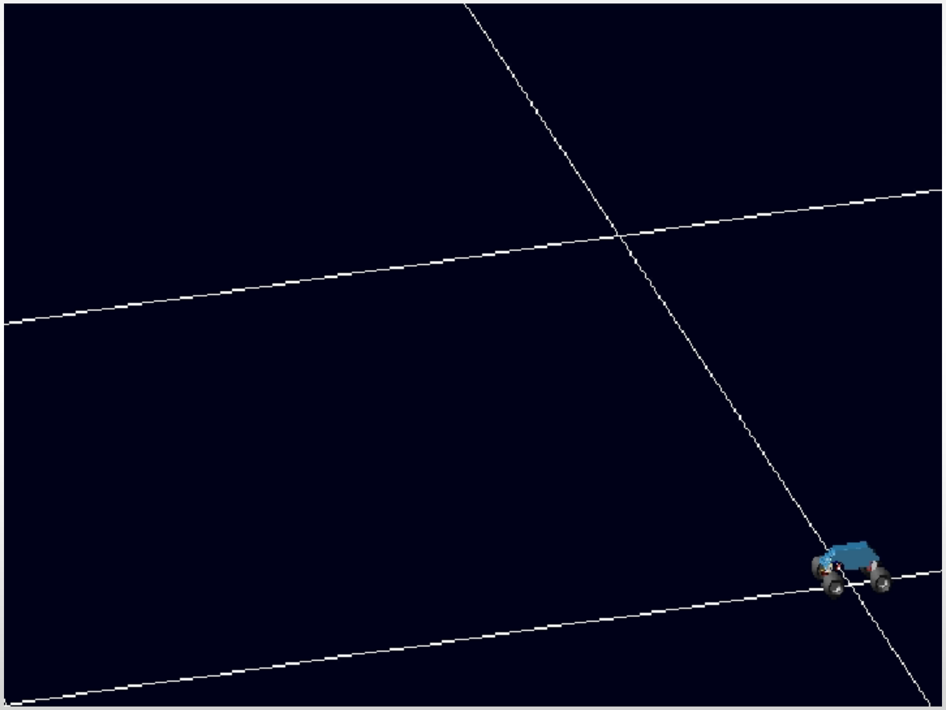
Maneuvering Inside Trajectory Space Constraints



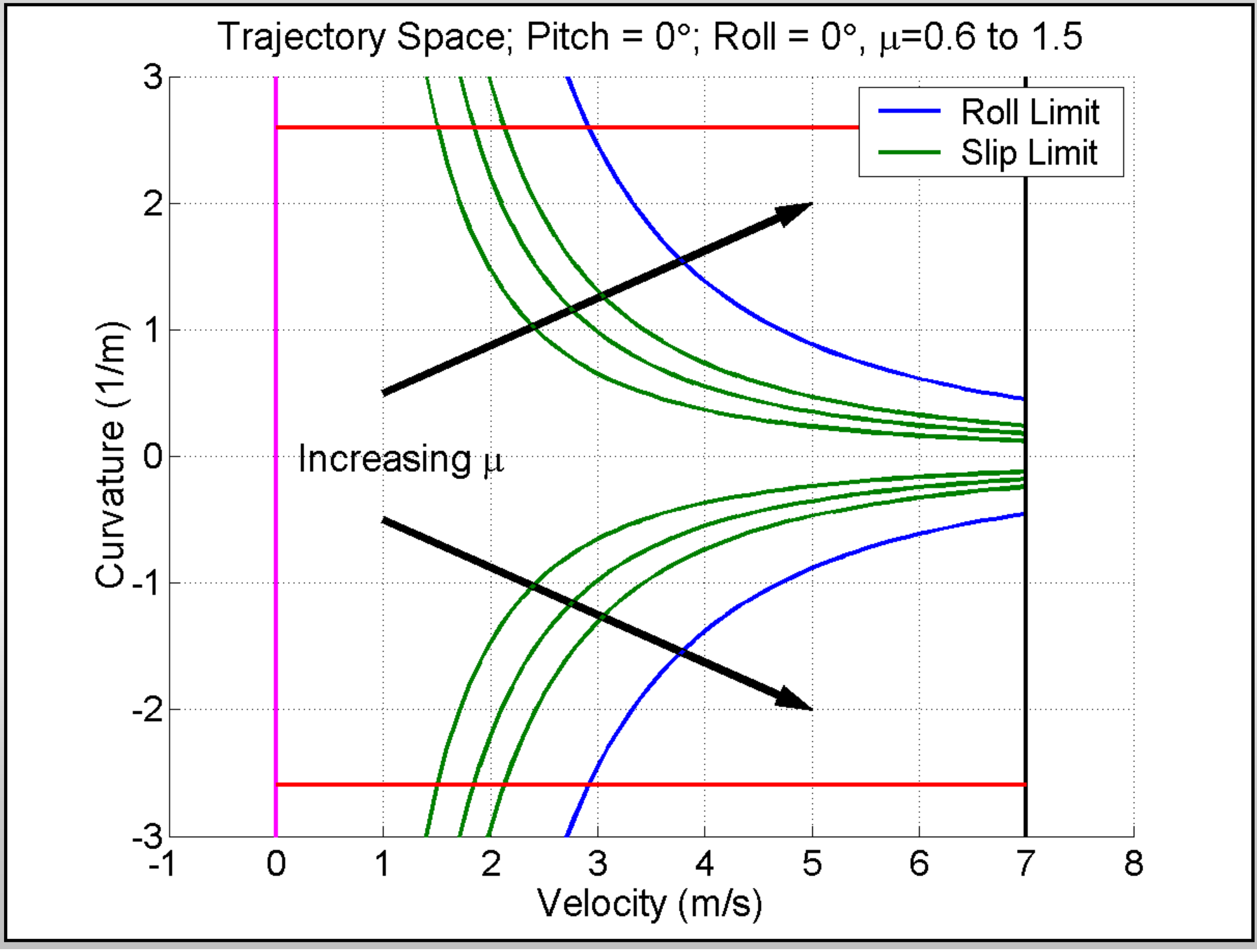


Maneuvering Outside Trajectory Space Constraints

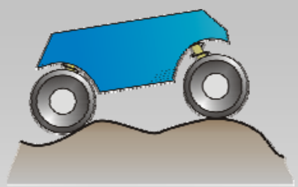


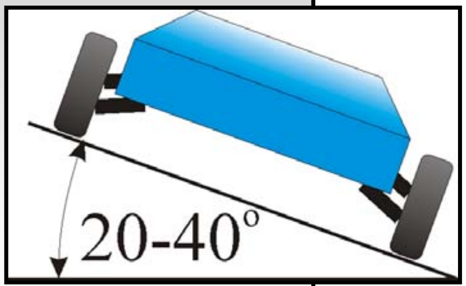


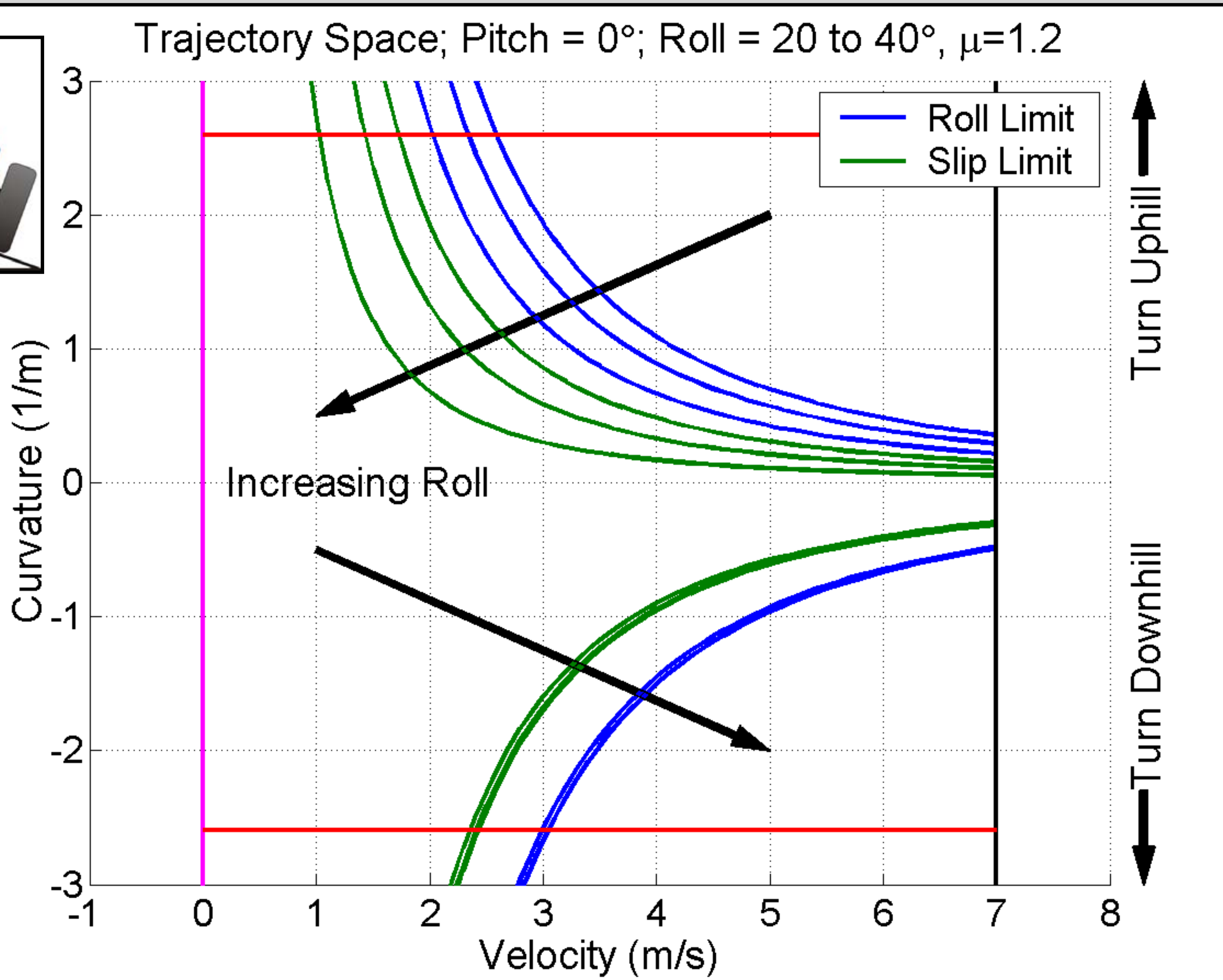
Effect of Terrain Conditions



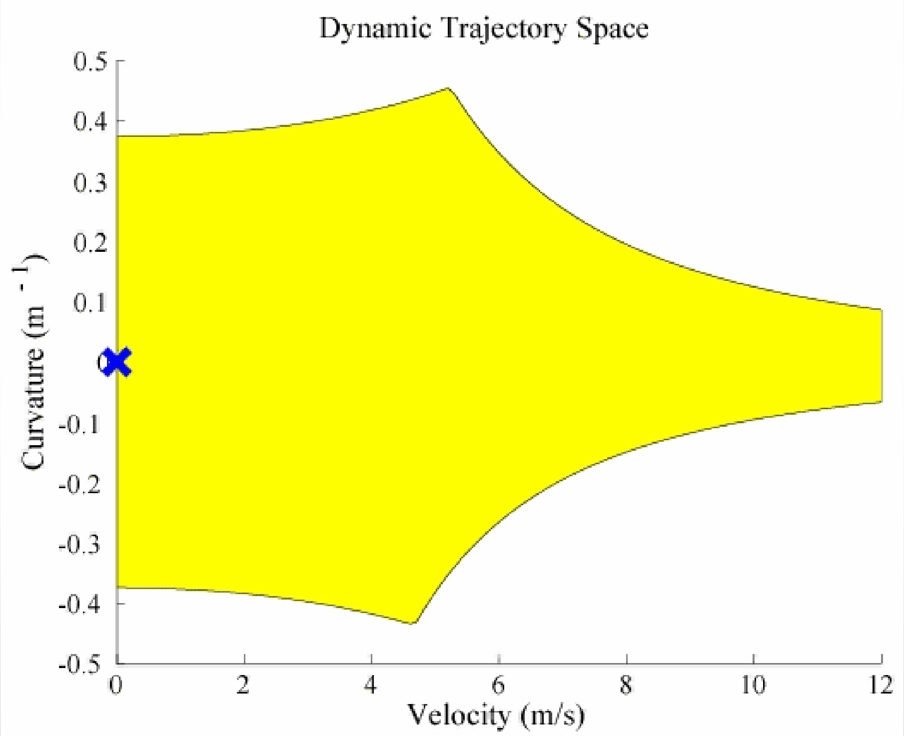
Effect of Terrain Unevenness

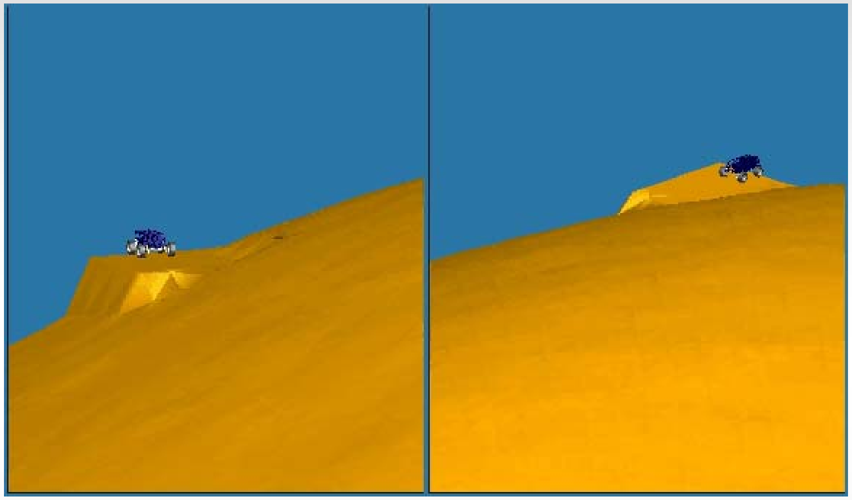


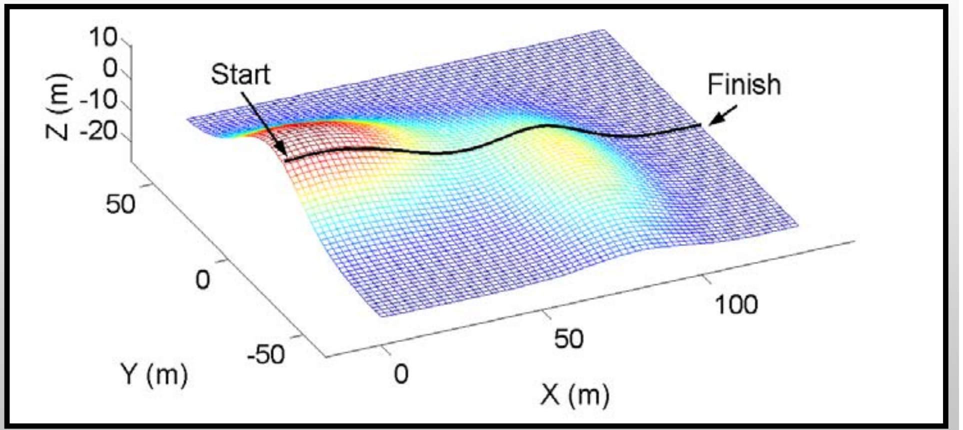




Dynamic Trajectory Space

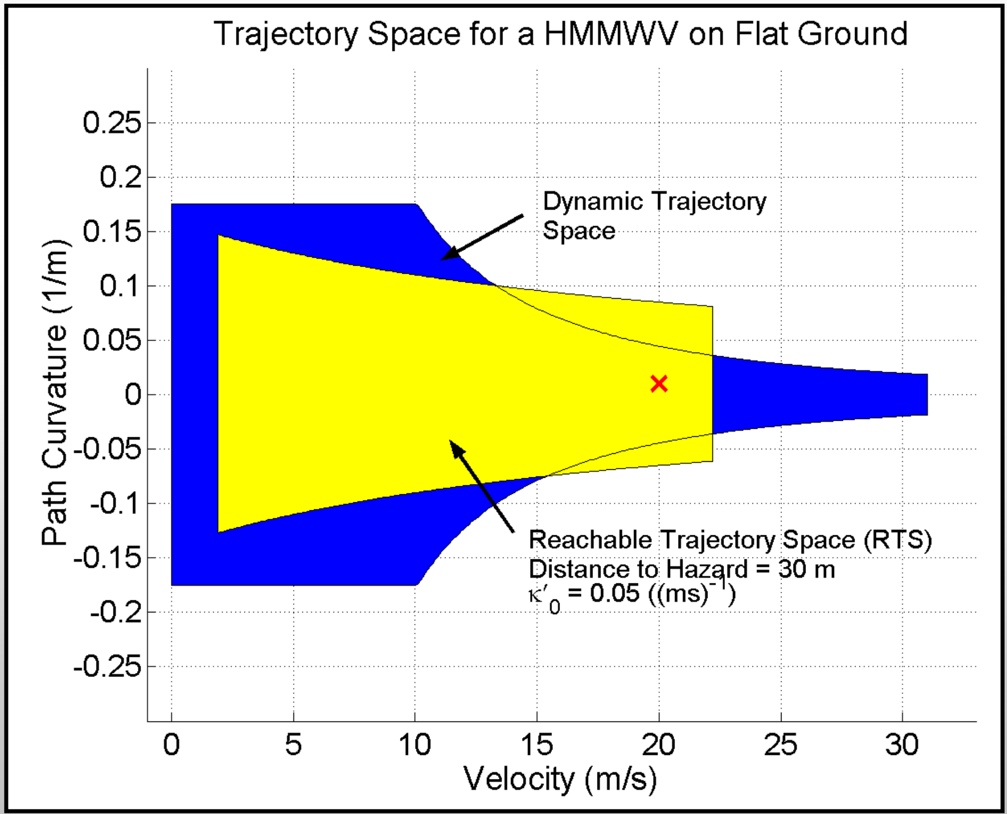






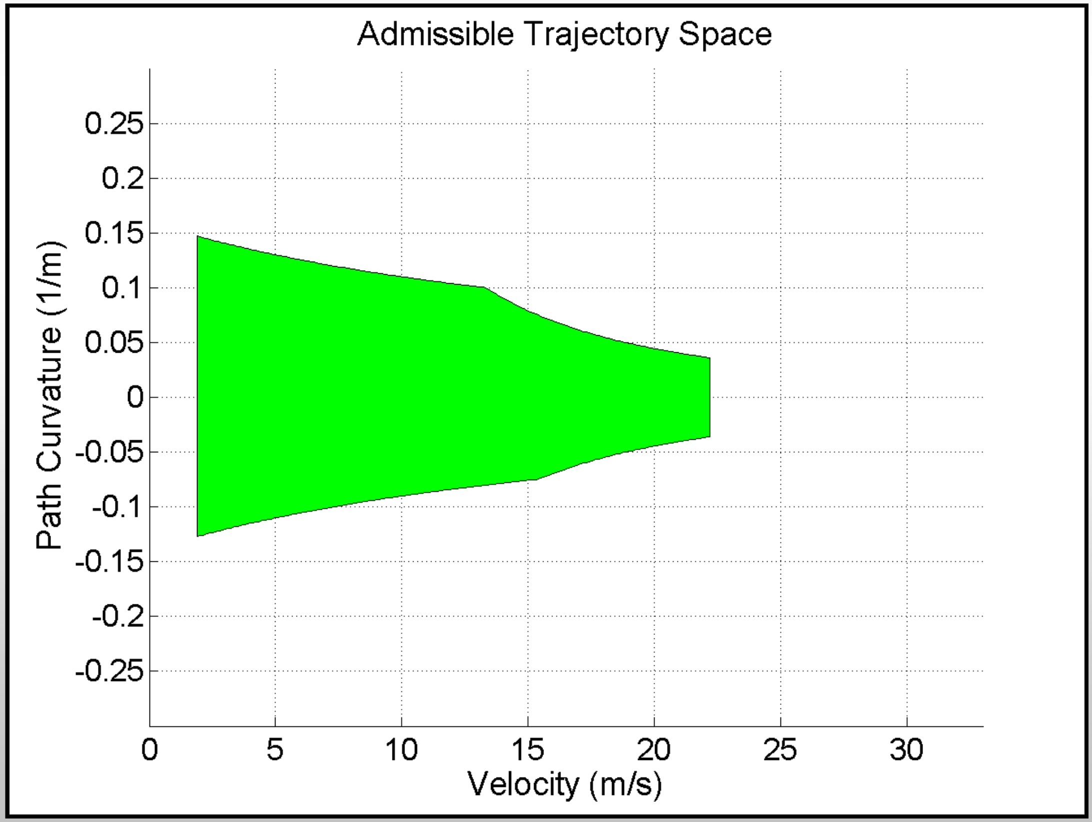
Reachable Trajectory Space, Λ

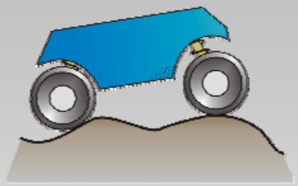
- The set of admissible velocity and curvature pairs a vehicle can transition to in a given time, *t*.



The Admissible Trajectory Space, Θ

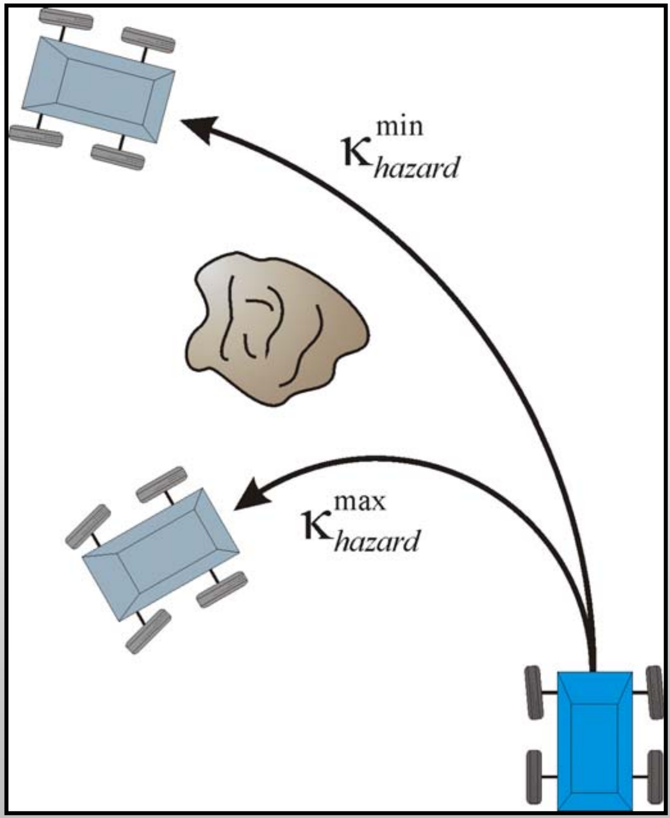
- The intersection of the dynamic trajectory space and the reachable trajectory space: $\boxed{\Theta = \Gamma \cap \Lambda}$

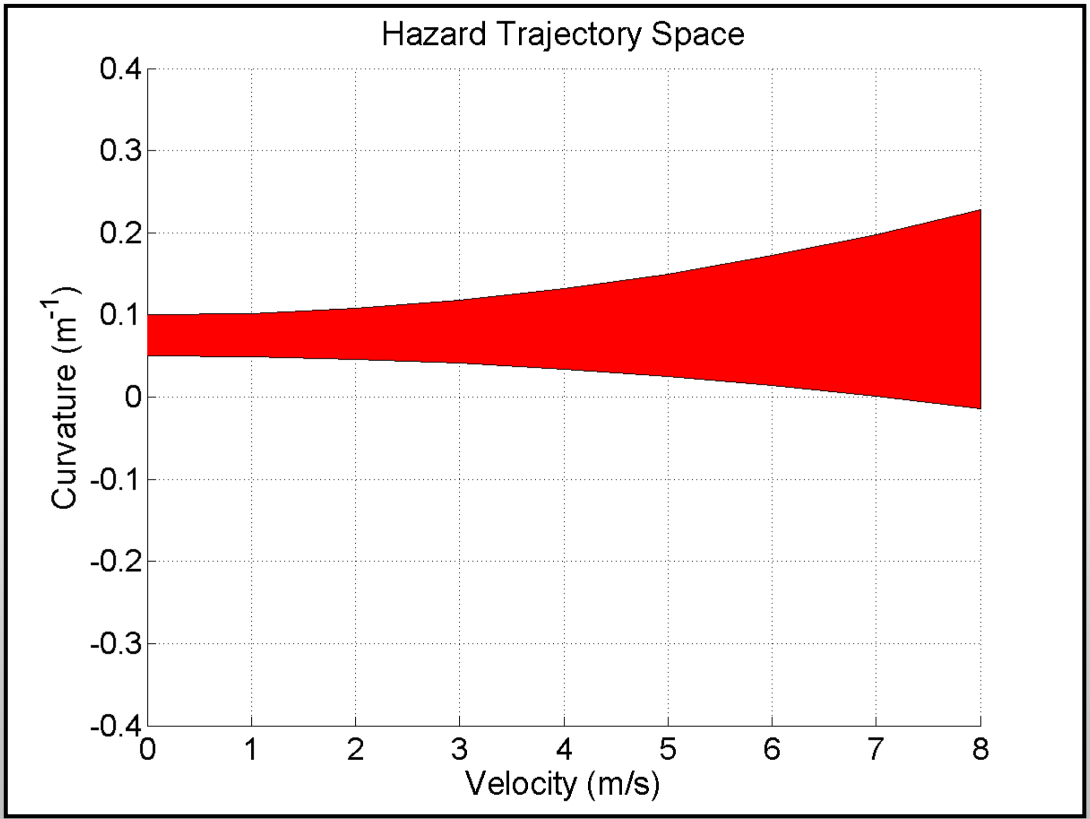


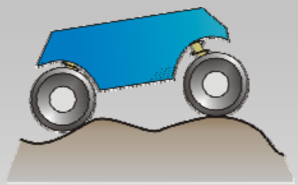


Hazard Trajectory Space, Ω

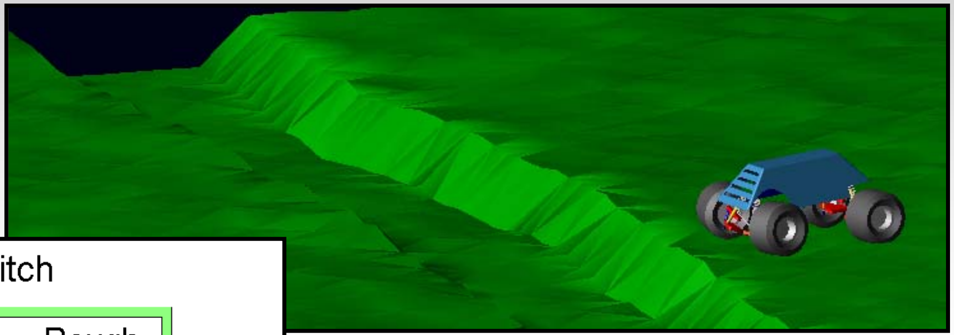
- The hazard trajectory space consists of velocity and curvature pairs that, if maintained, result in intersection with the hazard

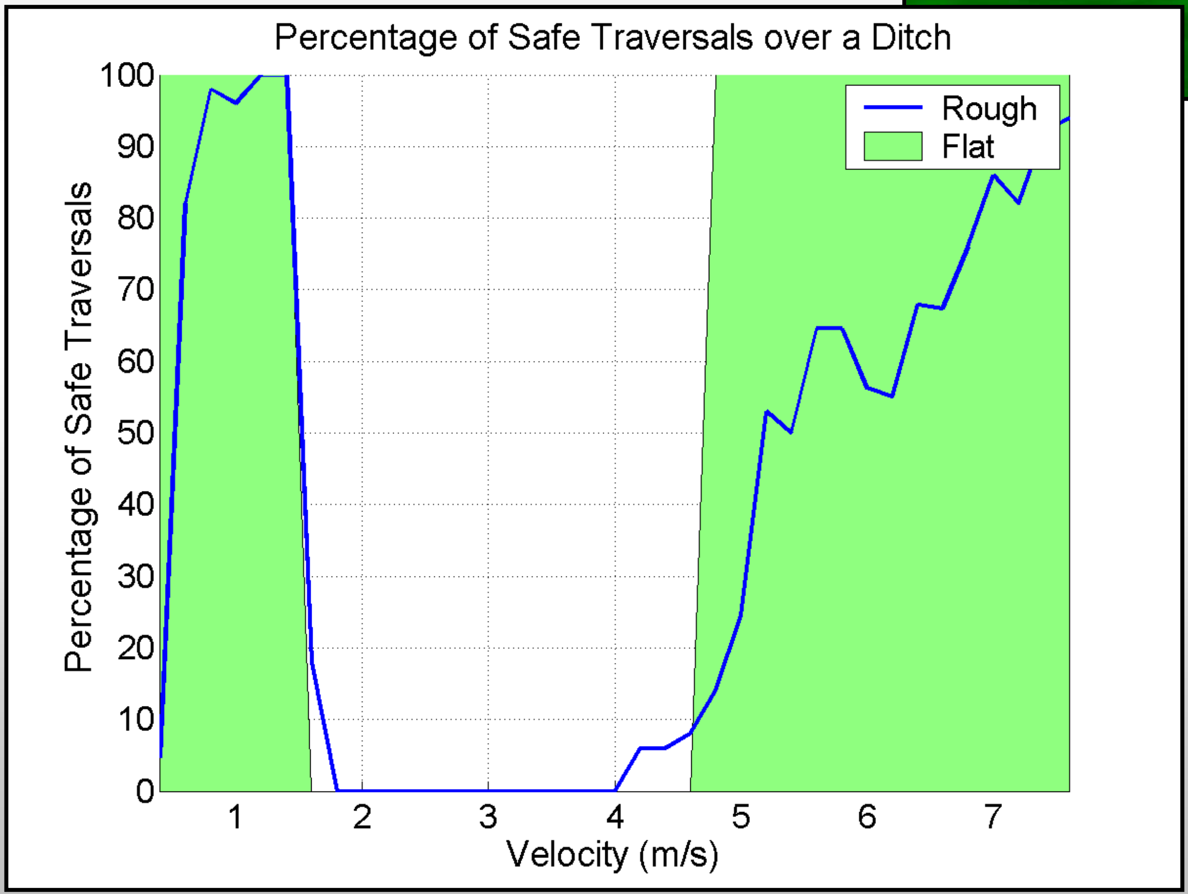




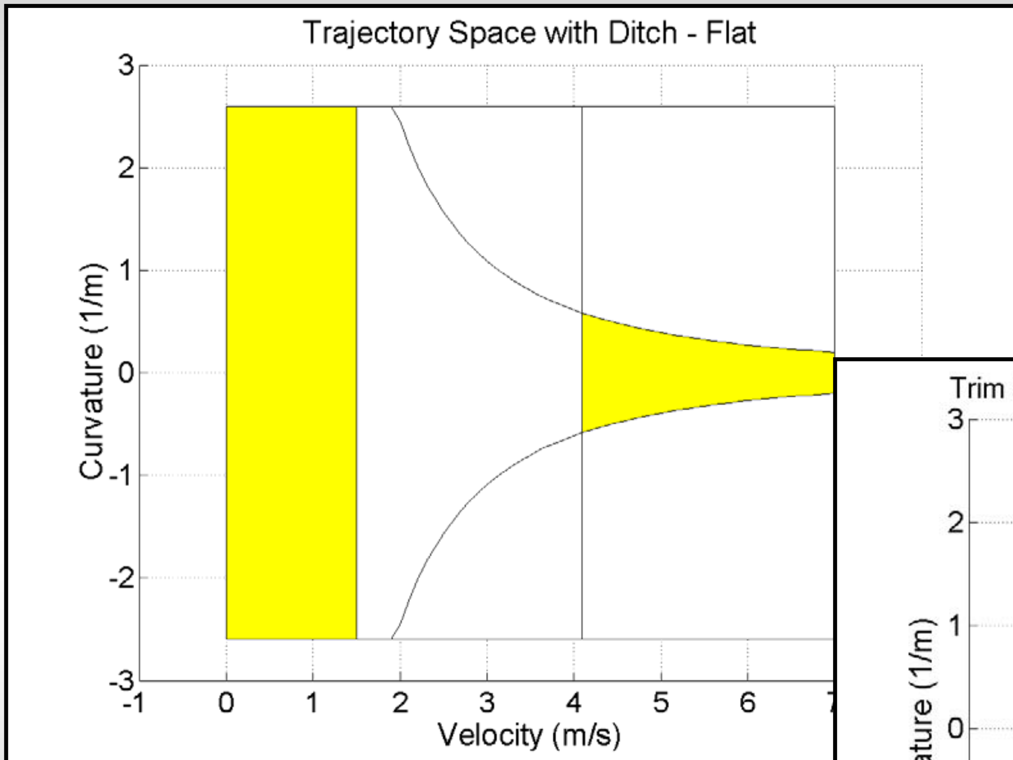


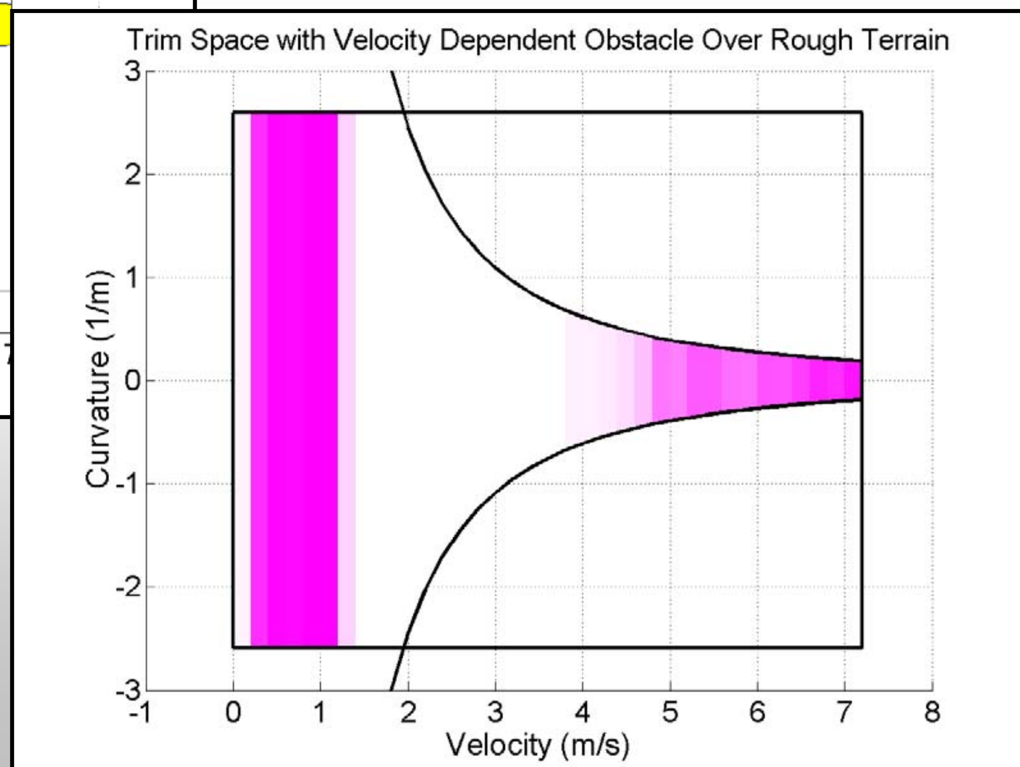
Roughness



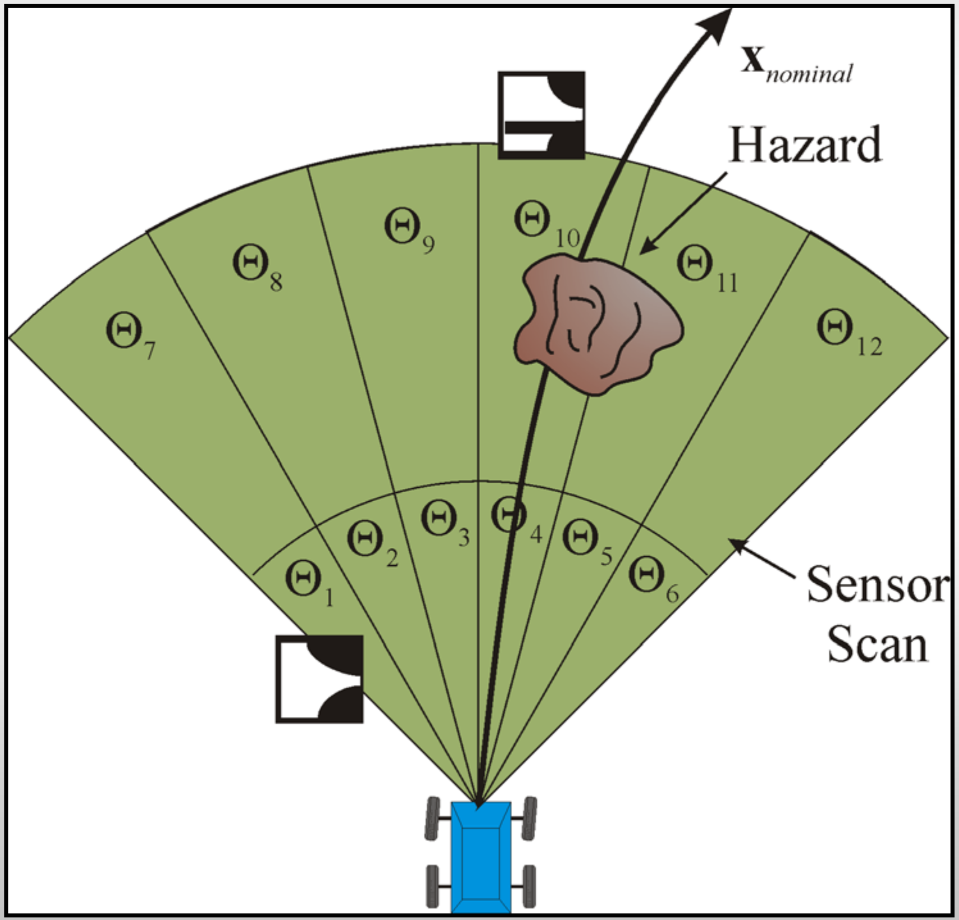

Percentage of Safe Traversals over a Ditch
Rough
Flat
Percentage of Safe Traversals
0
10
20
30
40
50
60
70
80
90
100
1
2
3
4
5
6
7
Velocity (m/s)

Roughness and the Trajectory Space

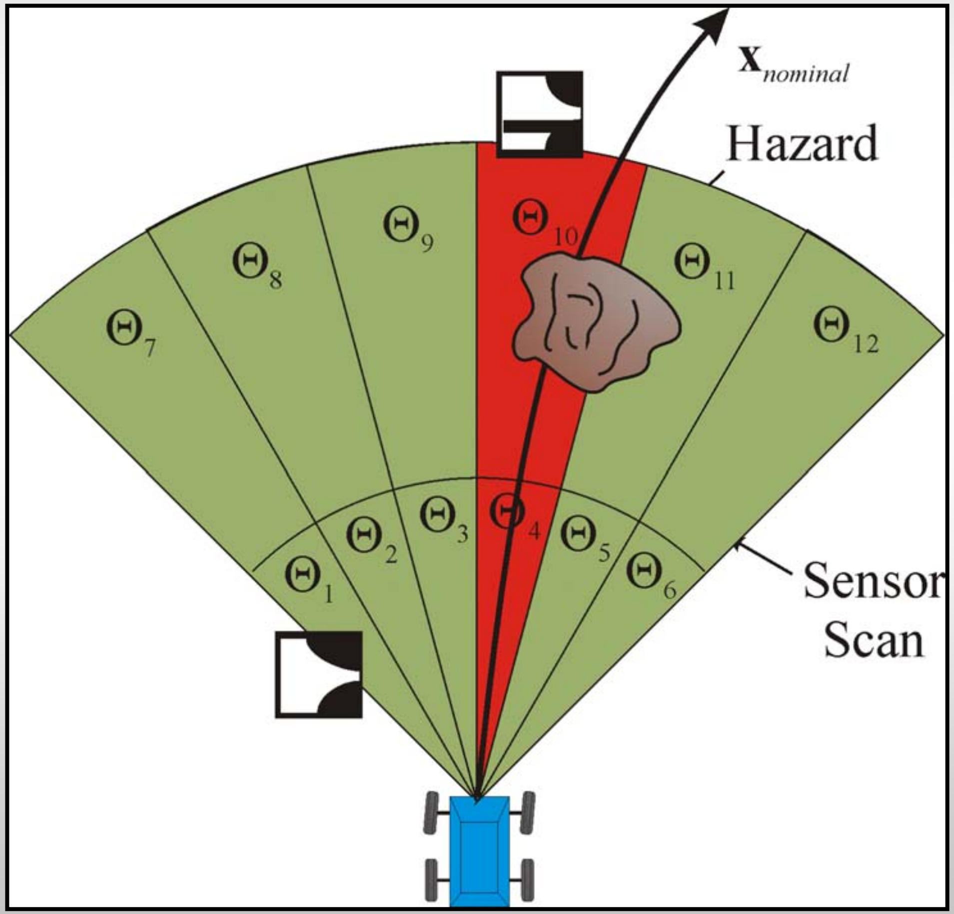


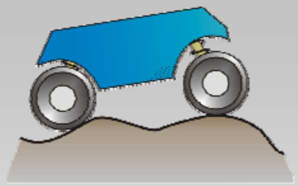


Hazard Avoidance Maneuver



When to Enact a Hazard Avoidance Maneuver





Maneuver Selection

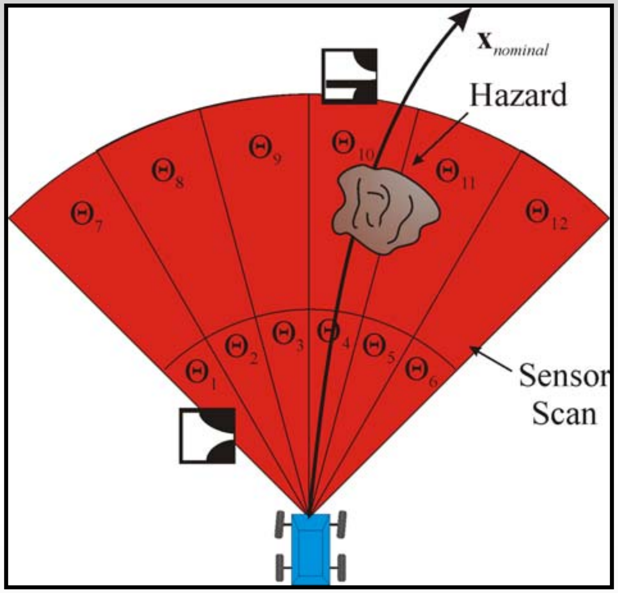
- Let the total admissible trajectory space be defined as:

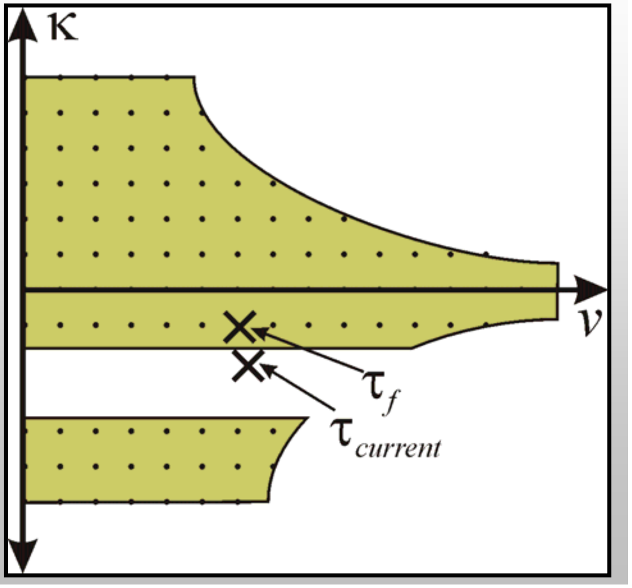
$$Z \equiv (\Theta_1 \cap \ldots \cap \Theta_n) - \Omega_1 - \ldots - \Omega_m$$

- Find: $\tau_f = (v_f, \kappa_f) \in Z$

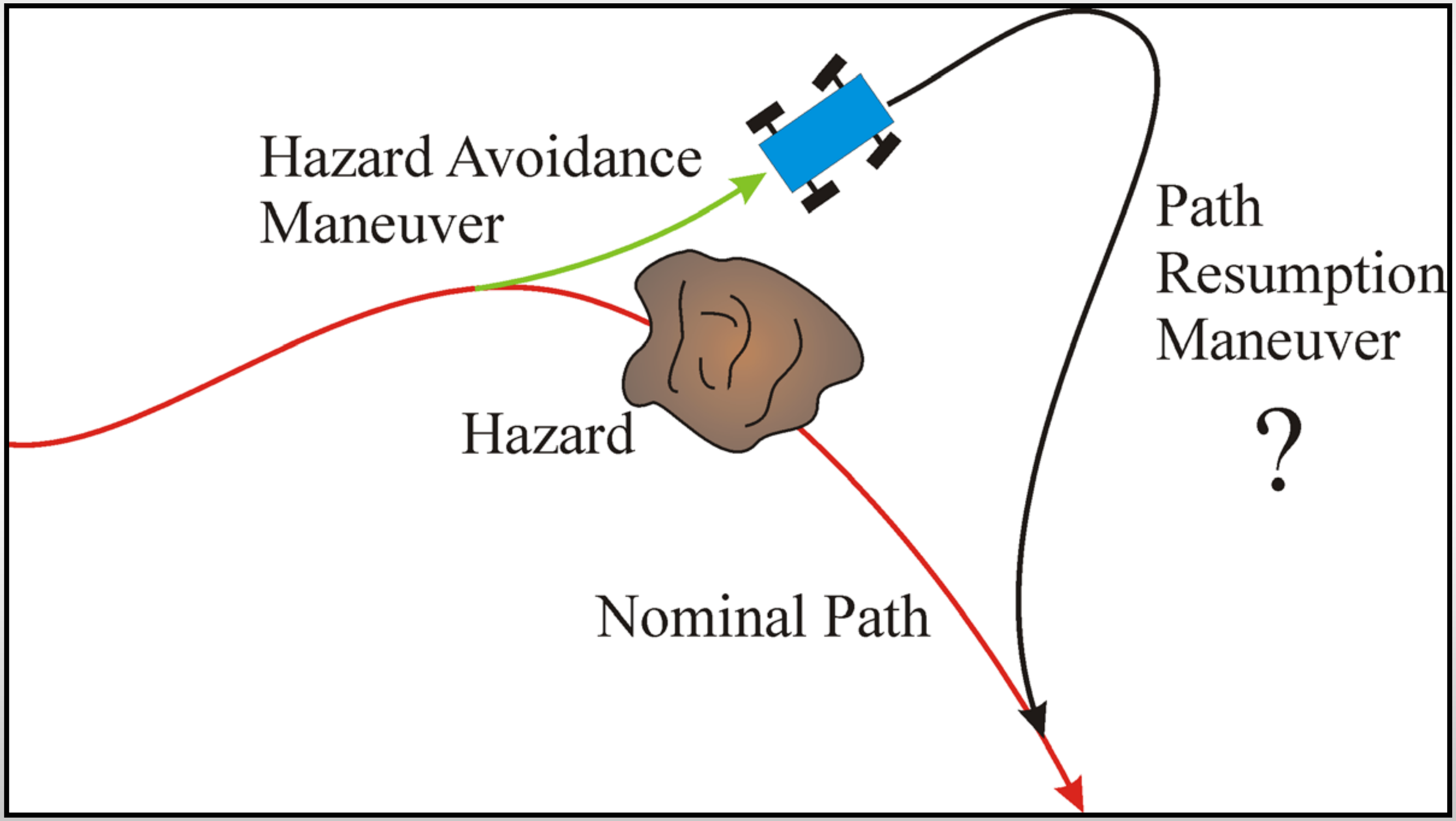
- Many possible methods
  - Discretize space
  - Minimize Δ

$$\Delta = \sqrt{\frac{K_1}{\kappa_{\max} - \kappa_{\min}}(\kappa_0 - \kappa_i)^2 + \frac{K_2}{v_{\max}}(v_0 - v_i)^2}$$

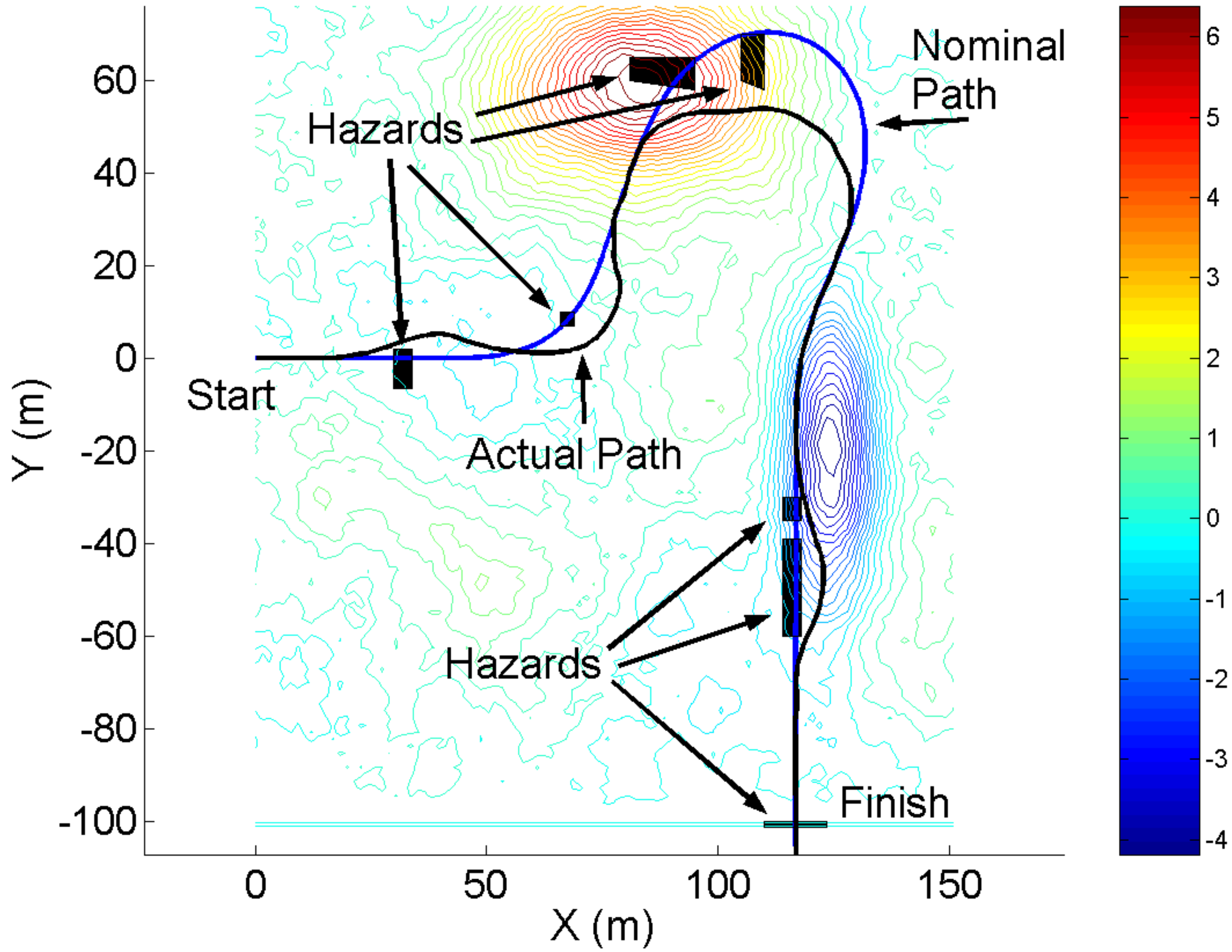




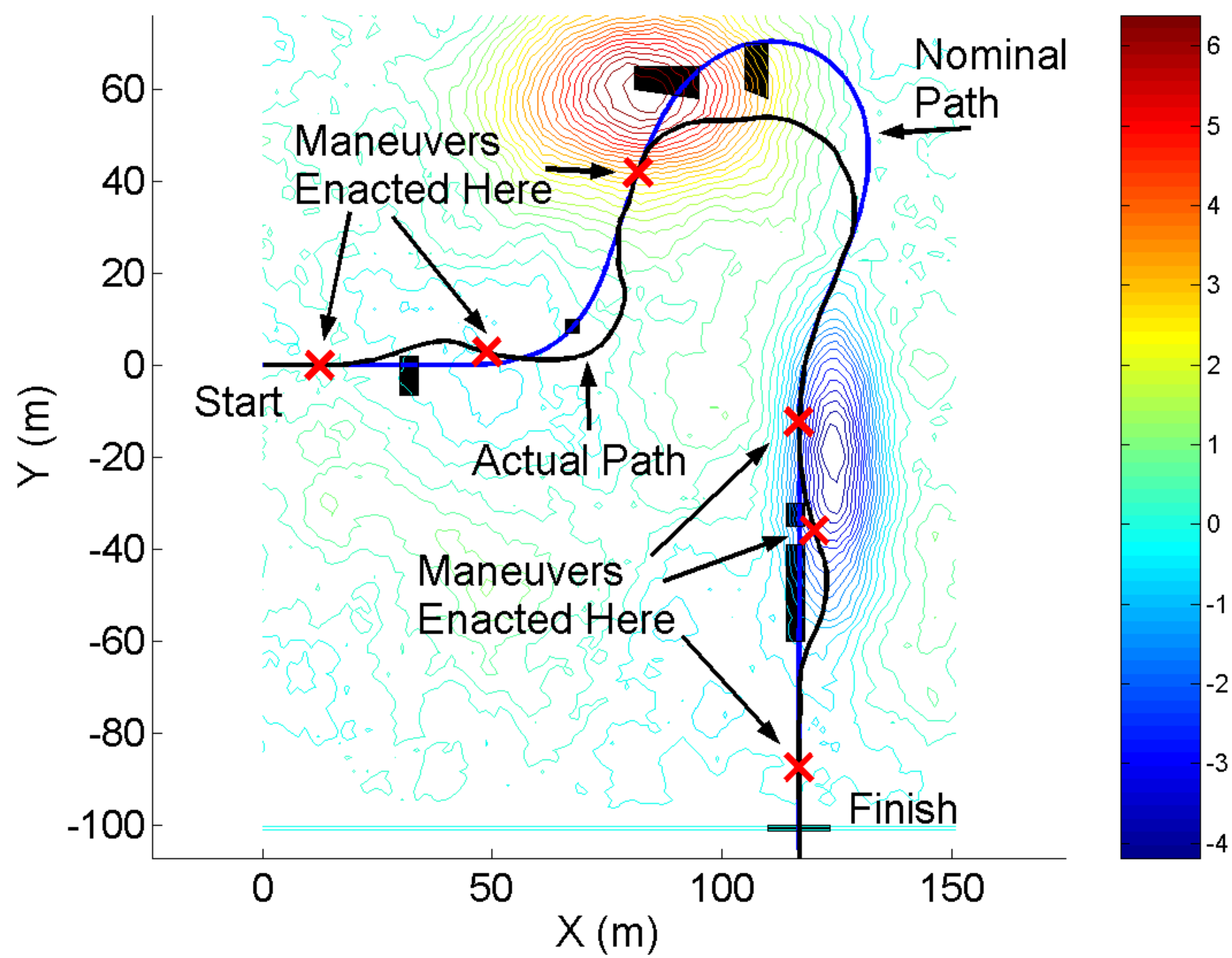
Path Resumption Maneuver



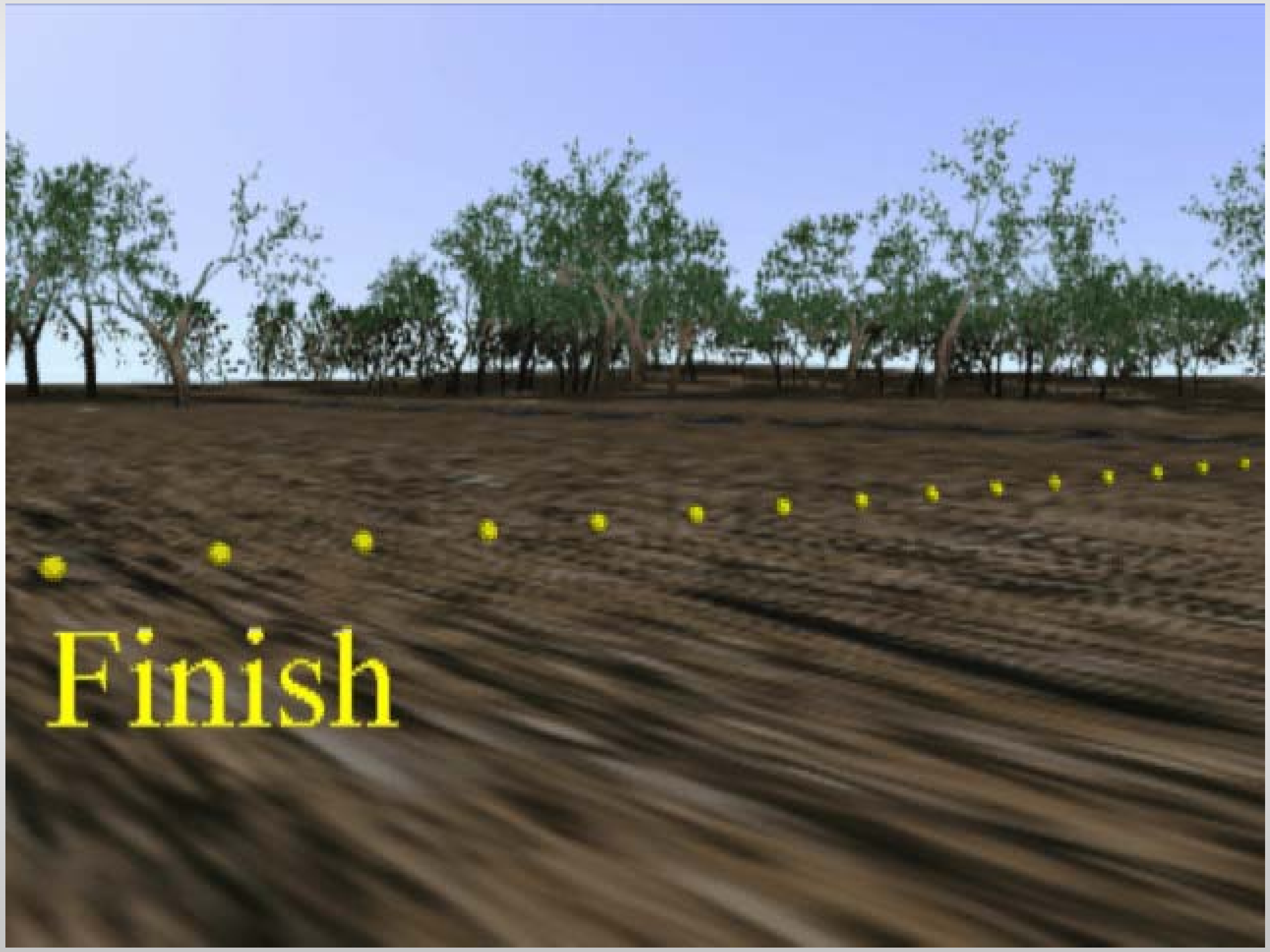
Hazard Avoidance on Rough Terrain Simulation Results



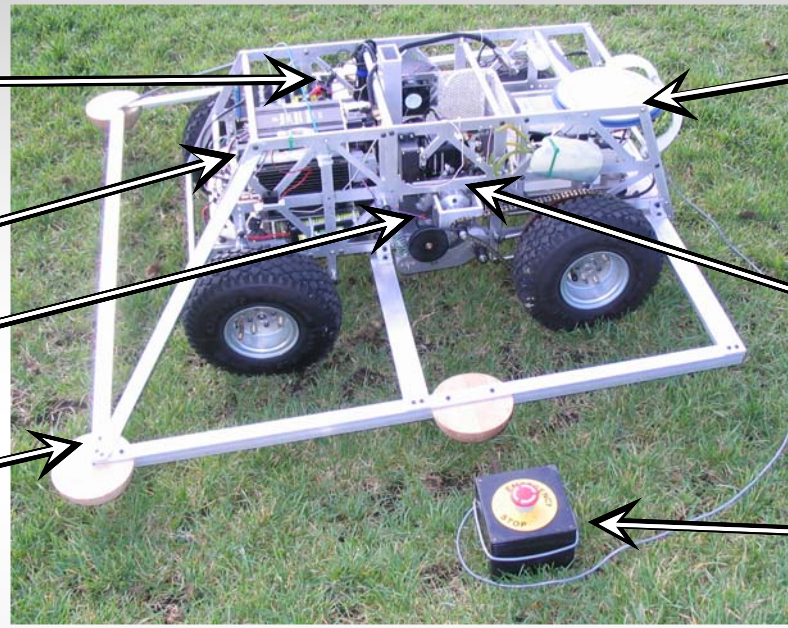
Hazard Avoidance on Rough Terrain Simulation Results



Hazard Avoidance on Rough Terrain Simulation Results

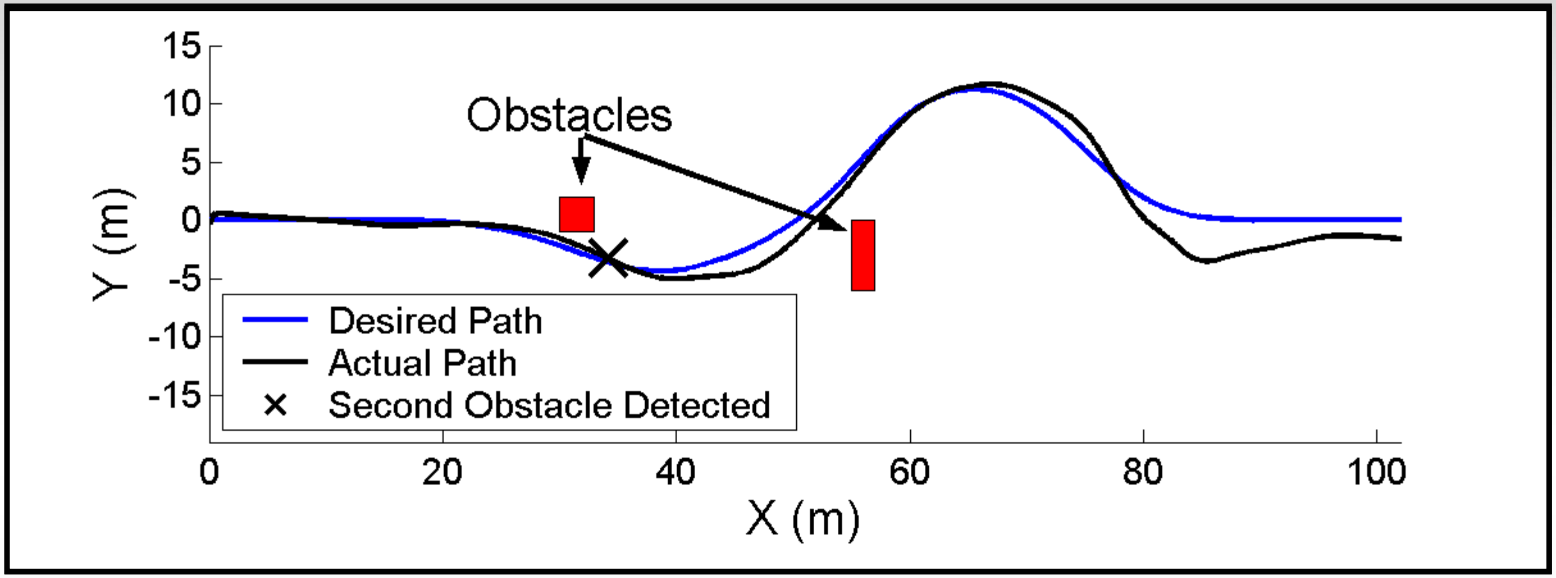


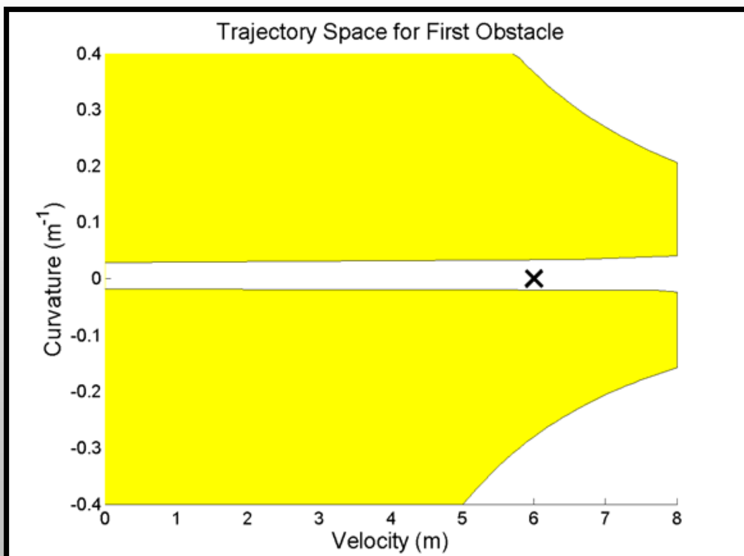
Autonomous Rough Terrain Experimental System (ARTEmiS)

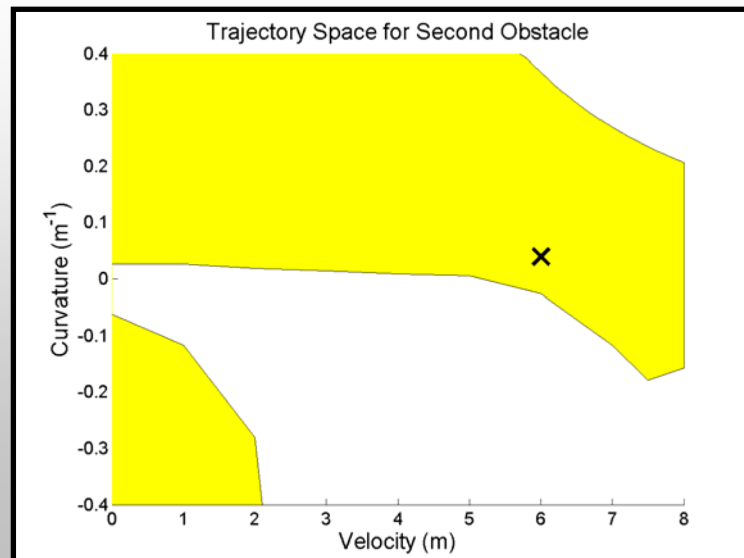


Experiment Title	Purpose
Multiple Hazards	Demonstrate high speed avoidance of serial hazards
Sloped Terrain	Sloped terrain affects choice of maneuver
Rough Terrain	Demonstrate algorithm on rough terrain

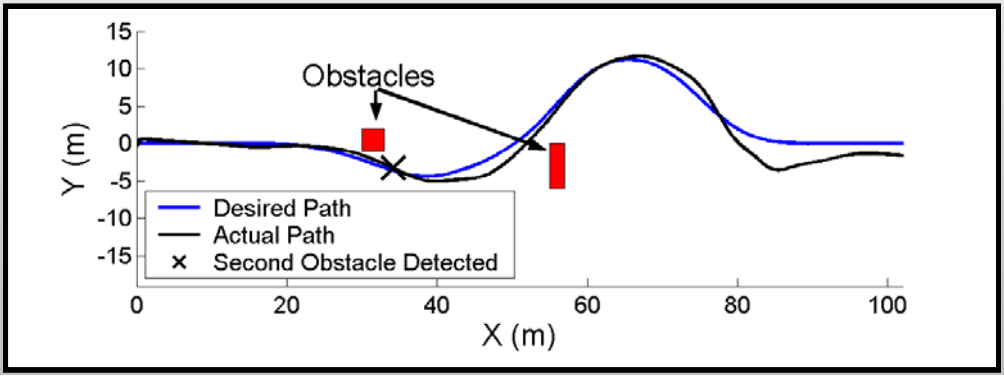
Multiple Hazard Avoidance Experimental Results

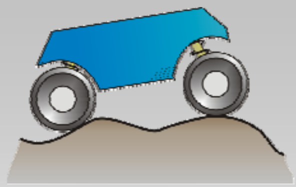






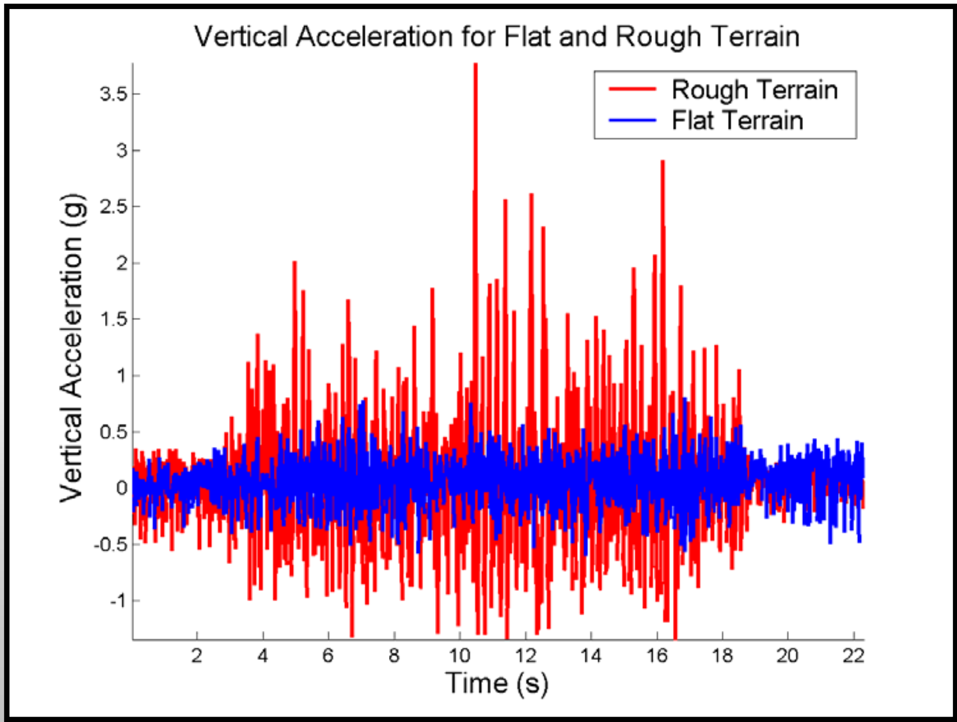
Multiple Hazard Avoidance Experimental Results



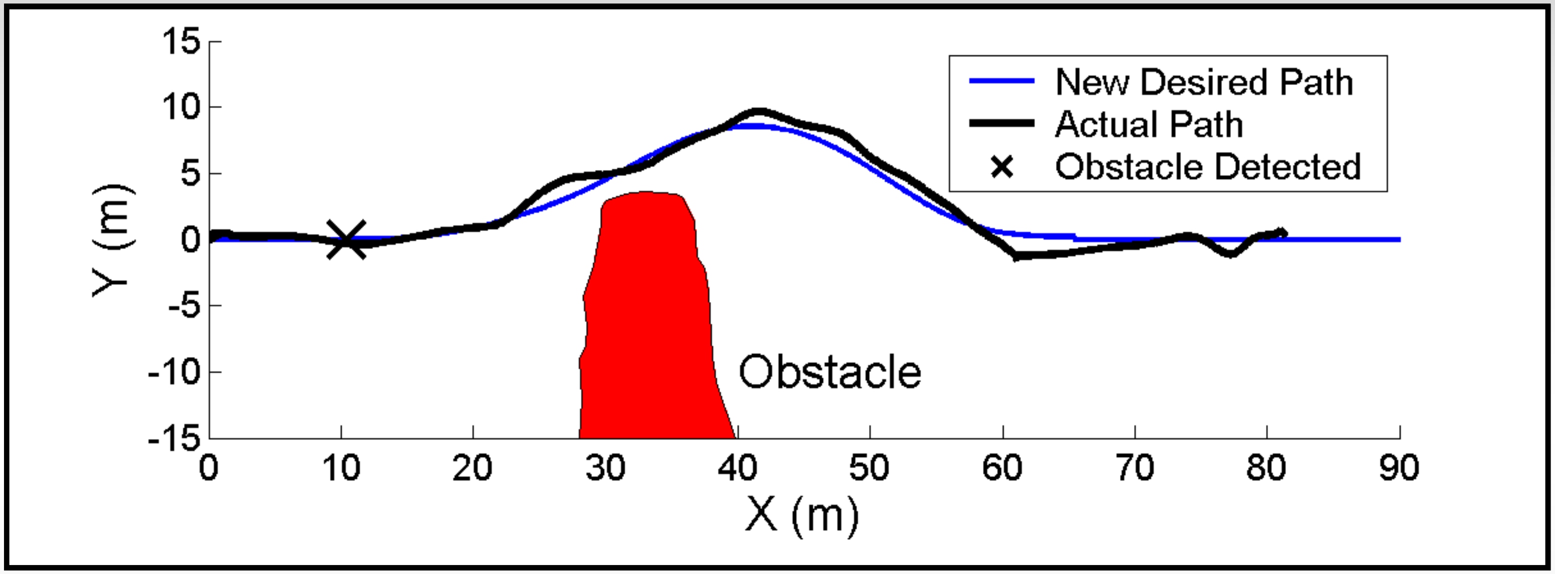


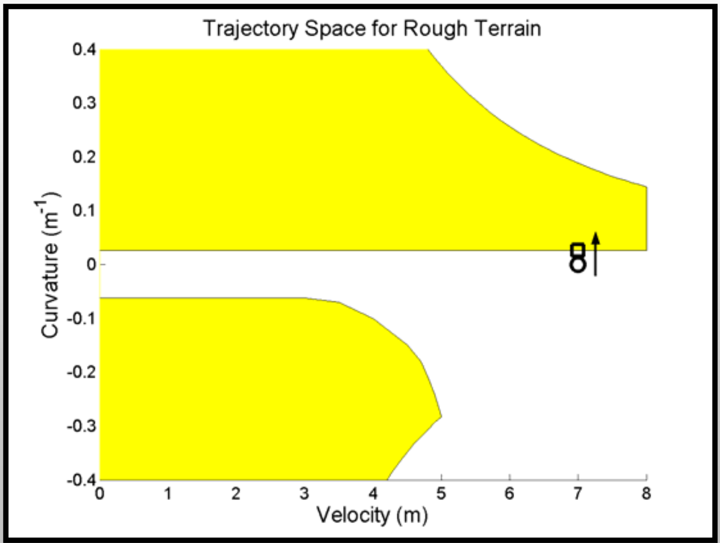
Rough Terrain Experimental Results

- Rough natural terrain
- Experiments run at speeds of 4 to 7 m/s
- Ballistic motion and wheel slip achieved



Rough Terrain Experimental Results



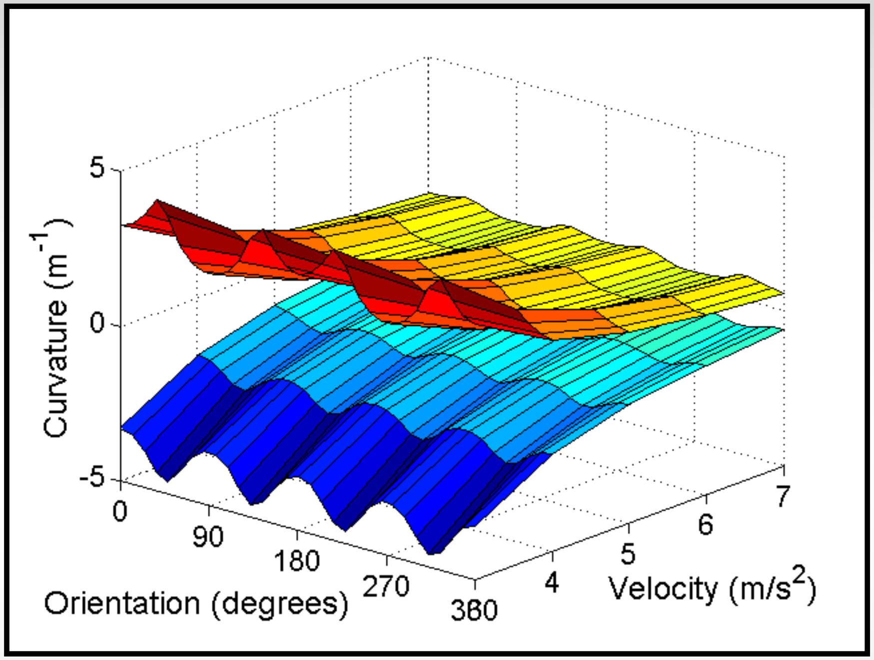


Rough Terrain Experimental Results

Conclusions and Future Work

- An effective physics-based hazard avoidance algorithm for emergency situations

- Extensions for omnidirectional vehicles
- Improved maneuver selection



Acknowledgments

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  - Prof. Yoji Kuroda
  - Shingo Shimoda
  - Prof. Guillaume Morel
  - Dariusz Golda

Sampling Based Model Predictive Control (SBMPC) with Application to Motion Planning in Extreme Environments

October 6, 2006

Damion Dunlap
Emmanuel Collins, Jr.

CISCOR
Center for Intelligent Systems, Control, and Robotics

Sampling Based Model Predictive Control

KEY FEATURES:

➢Model Predictive Control (MPC) accomplishes motion planning in the presence of constraints using dynamic models.

➢These constraints may include:

- obstacles, stability constraints, limitations on actuator amplitude, maximum vibration amplitude, etc.

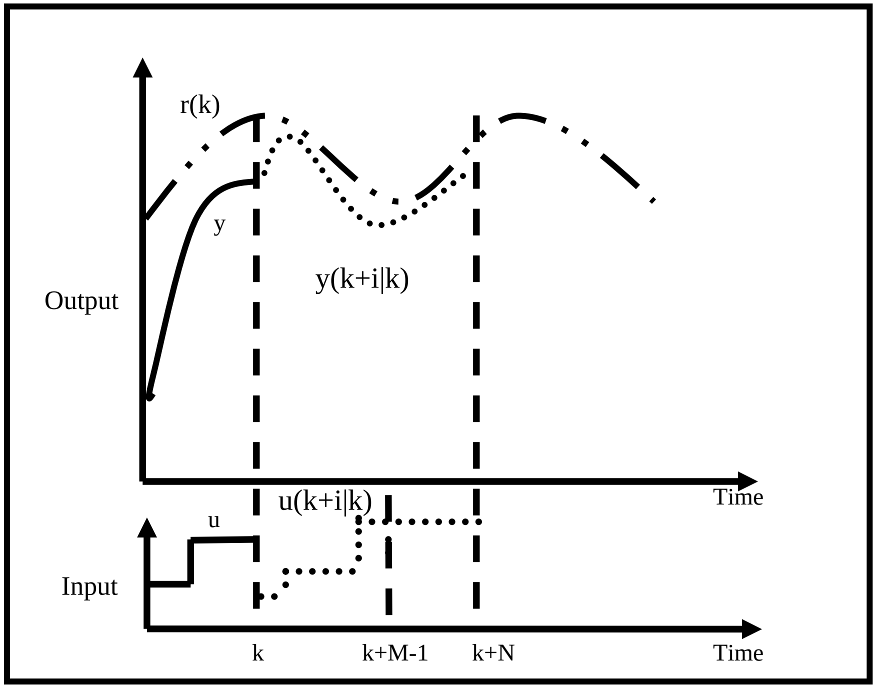
➢The dynamic models allow path planning to rigorously take into account:

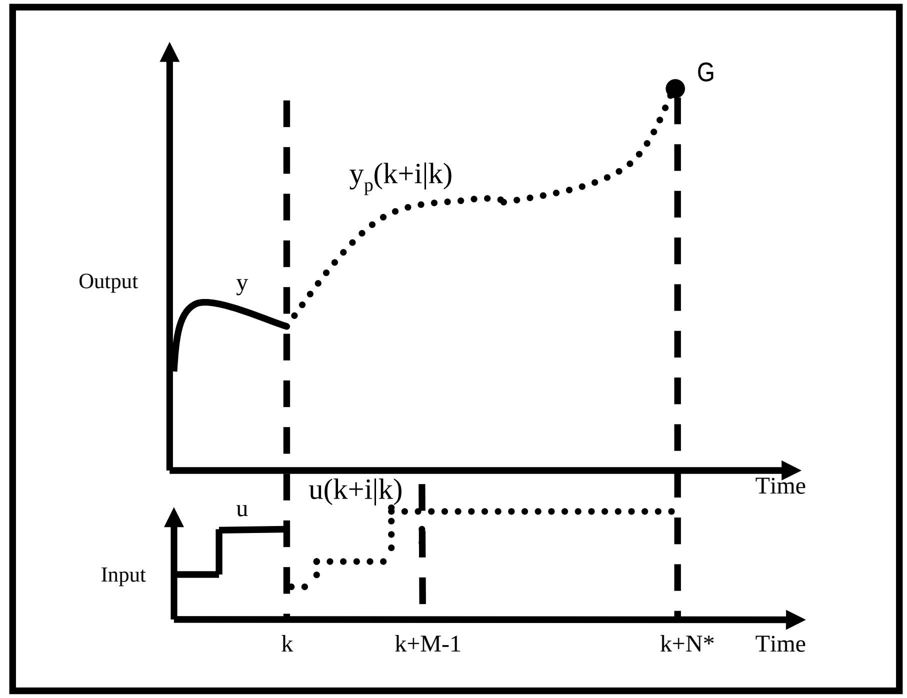
- vehicle kinematics, slip, energy consumption, complex motion (e.g., when climbing complex objects), terrain type, the calculation of time-dependent paths (position, velocity, & acceleration), dynamic obstacles, etc.

➢A key step in one approach to making MPC computationally tractable for AGVs is the sampling of the model input space (usually consisting of forces and torques).

➢Sampling Based MPC can also exploit "differential flatness" for computational efficiency.

Receding Horizon MPC vs Shrinking Horizon MPC





$$\min_{u} J = \sum_{i=1}^{N} \left\| r(k+i) - y(k+i) \right\|_Q^2 + \sum_{i=0}^{M-1} \left\| u(k+i) \right\|_S^2$$

$$\min_{u} J = \sum_{i=1}^{N^*} \left\| G - y(k+i) \right\|_Q^2 + \sum_{i=0}^{M-1} \left\| u(k+i) \right\|_S^2$$

Horizon Window

k	1	2	3	4	5	6
[illegible]						

N = 3

Horizon Window

k	1	2	3	4	5	6
[illegible]						

N^* = 6

Optimization Problem for Sampling Based MPC (SBMPC)

Given a system model:

$$\dot{x}(t) = f(x(t), u(t)), \;\; x(0) = x_0$$

$$y(t) = h(x(t))$$

solve the optimization problem:

$$\min_u J = \underbrace{\sum_{i=1}^{N} (y_{i+1} - y_i)^T Q (y_{i+1} - y_i)}_{\text{Distance to Goal (for } Q=I\text{)}} + \sum_{i=1}^{N} u_i^T R u_i$$

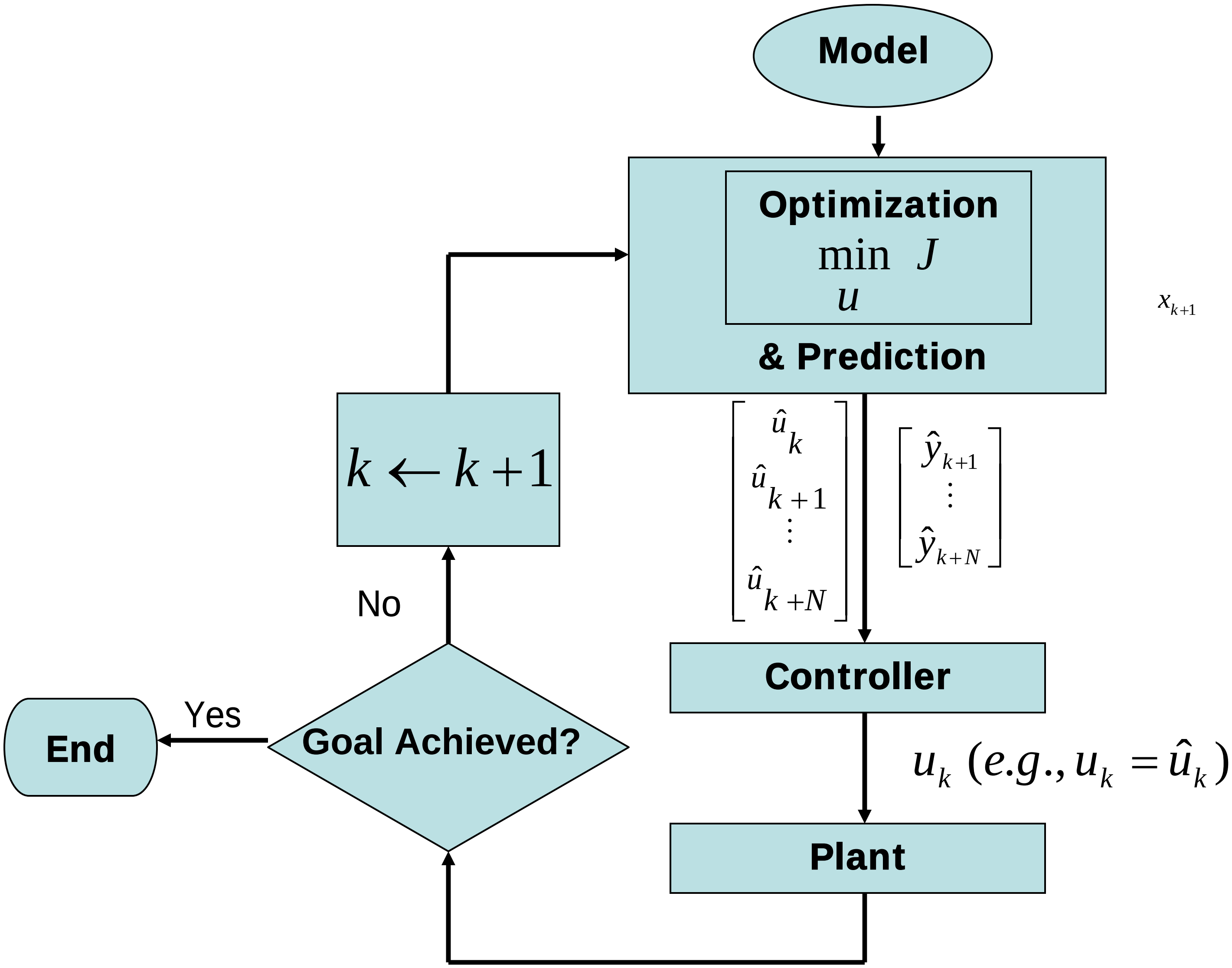
subject to

$$y_k \in \mathbf{G} \text{ for } k = N \text{ or } k = k_{\min}$$

$$x_k \in \mathbf{Q}_{free} \; \forall k \text{ (avoid obstacles, satisfy velocity constraints, etc.)}$$

$$u_k \in [u_{\min} \; u_{\max}] \;\; \forall k$$

SBMPC Predictive Control Overview



Focus on the Optimization & Prediction Process

- The following slides focus on the optimization and prediction process using input sampling:

Optimization

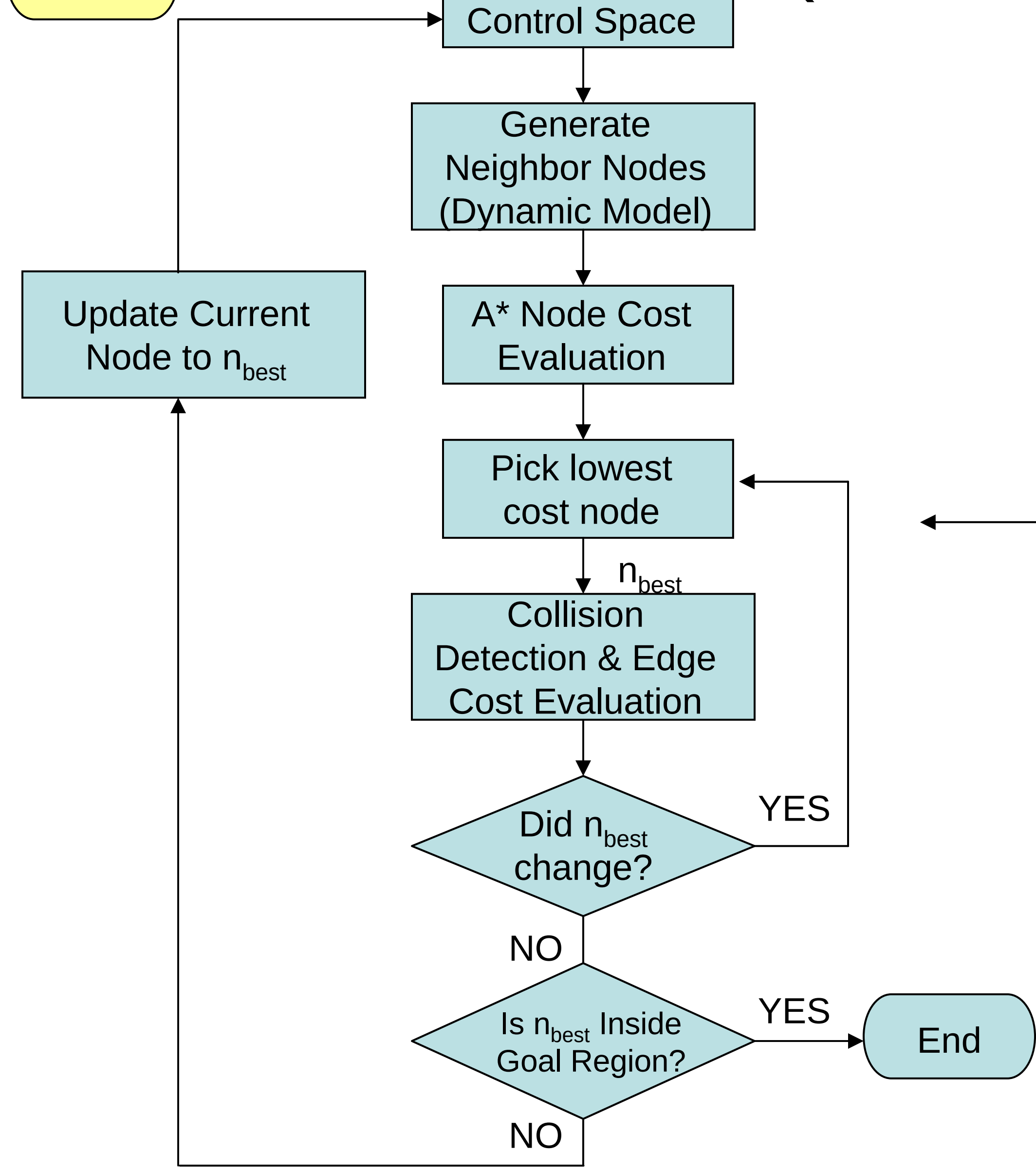
$$\min_{u} \; J$$

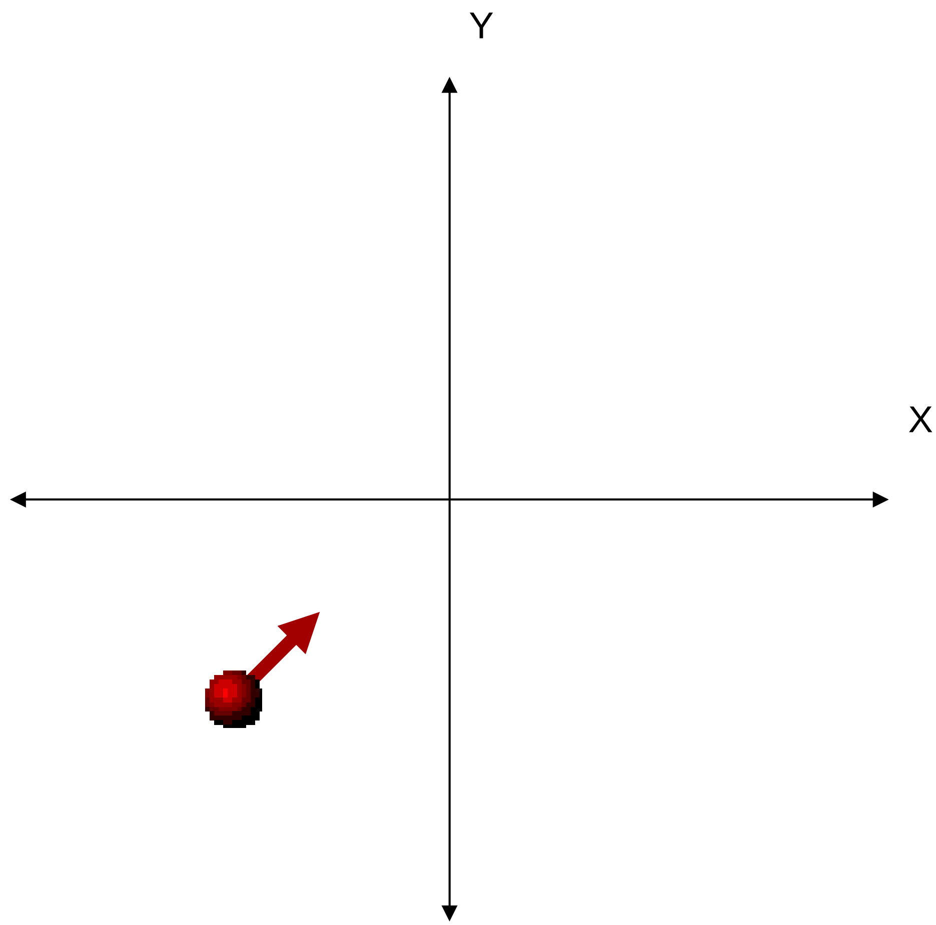
&

Prediction

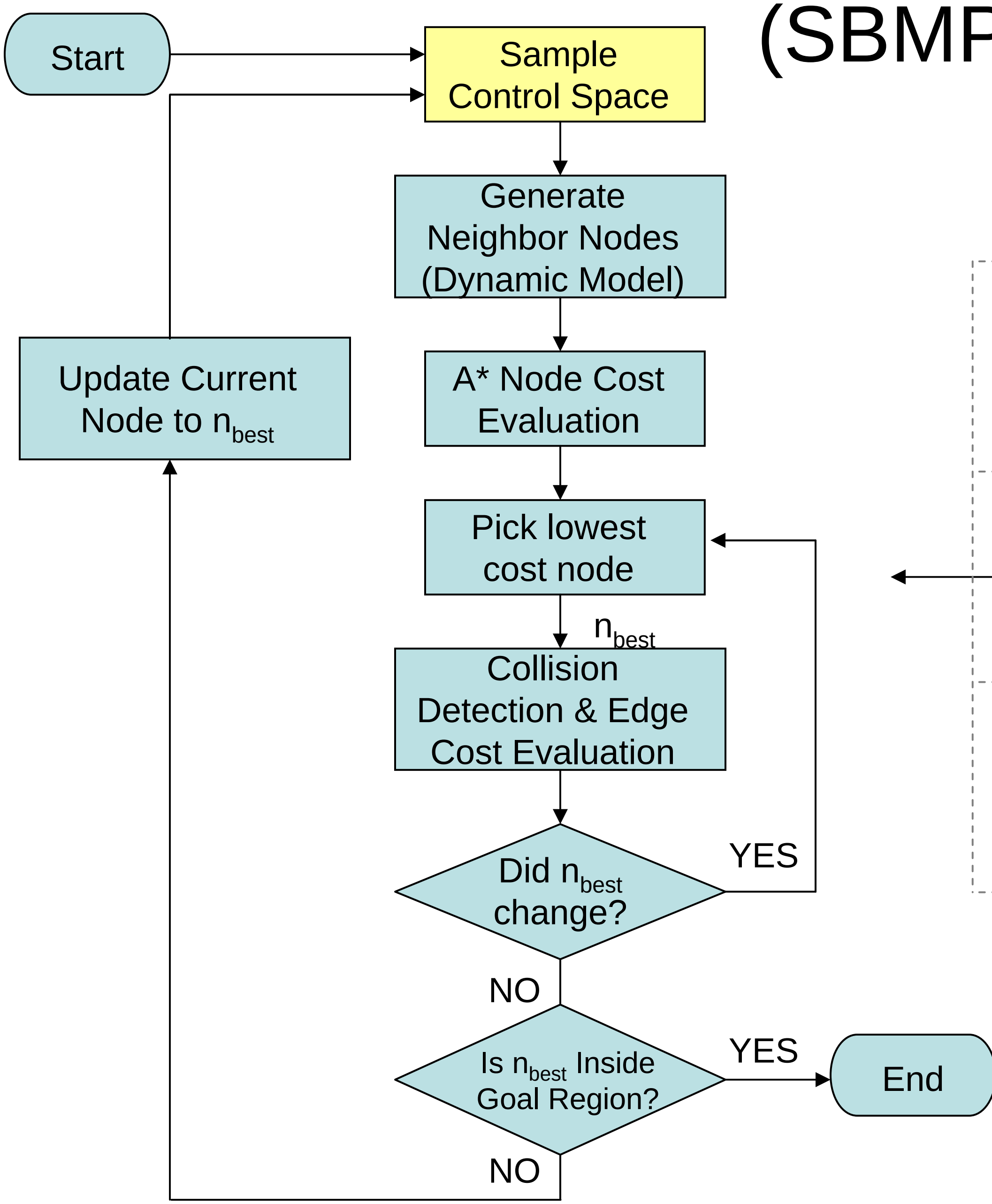
- The optimization is A* optimization.
  - It will always yield the global minimum subject to the constraints of input sampling.
  - The algorithm is resolution complete.
  - As the sampling increases, (if done properly) a feasible path will be found when one exists with probability one.
  - Computational speed can be greatly increased for some applications (e.g., high speed maneuvering on a flat surface) by precomputing the A* costs).
- Because the optimization is performed repeatedly, it can benefit computationally from a variation of A* called “Dynamic A*.”

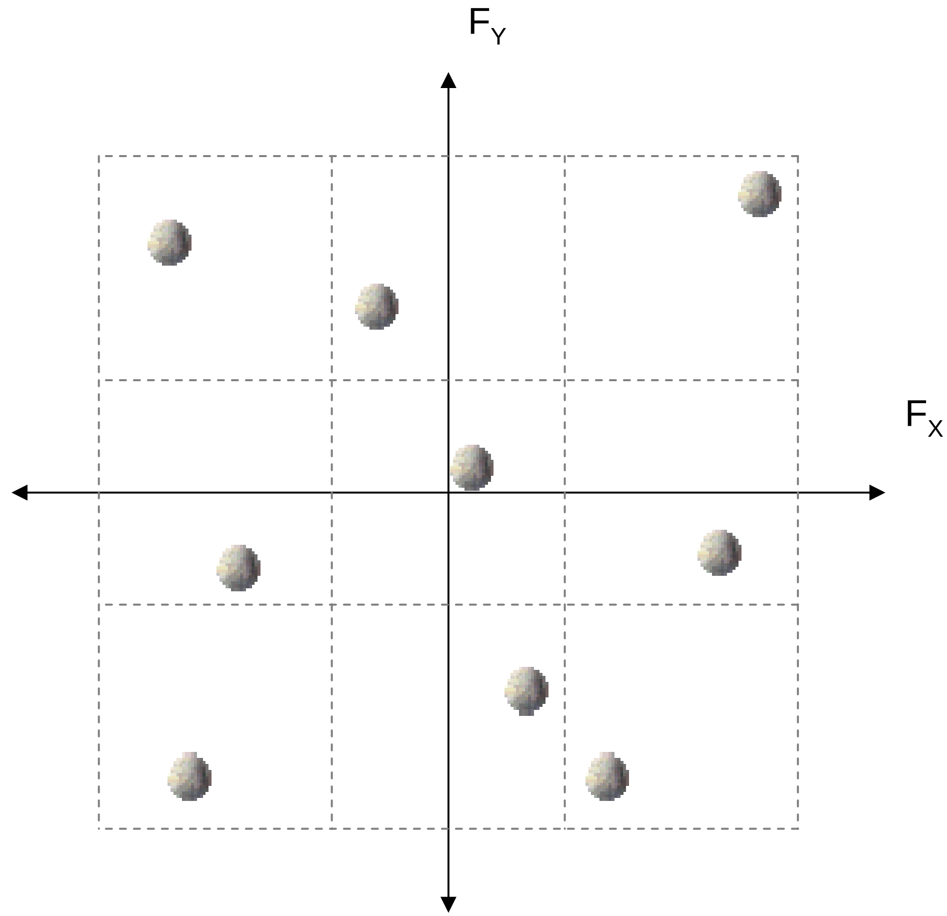
Sampling Based Model Predictive Optimization (SBMPO)





Sampling Based Model Predictive Optimization (SBMPO)





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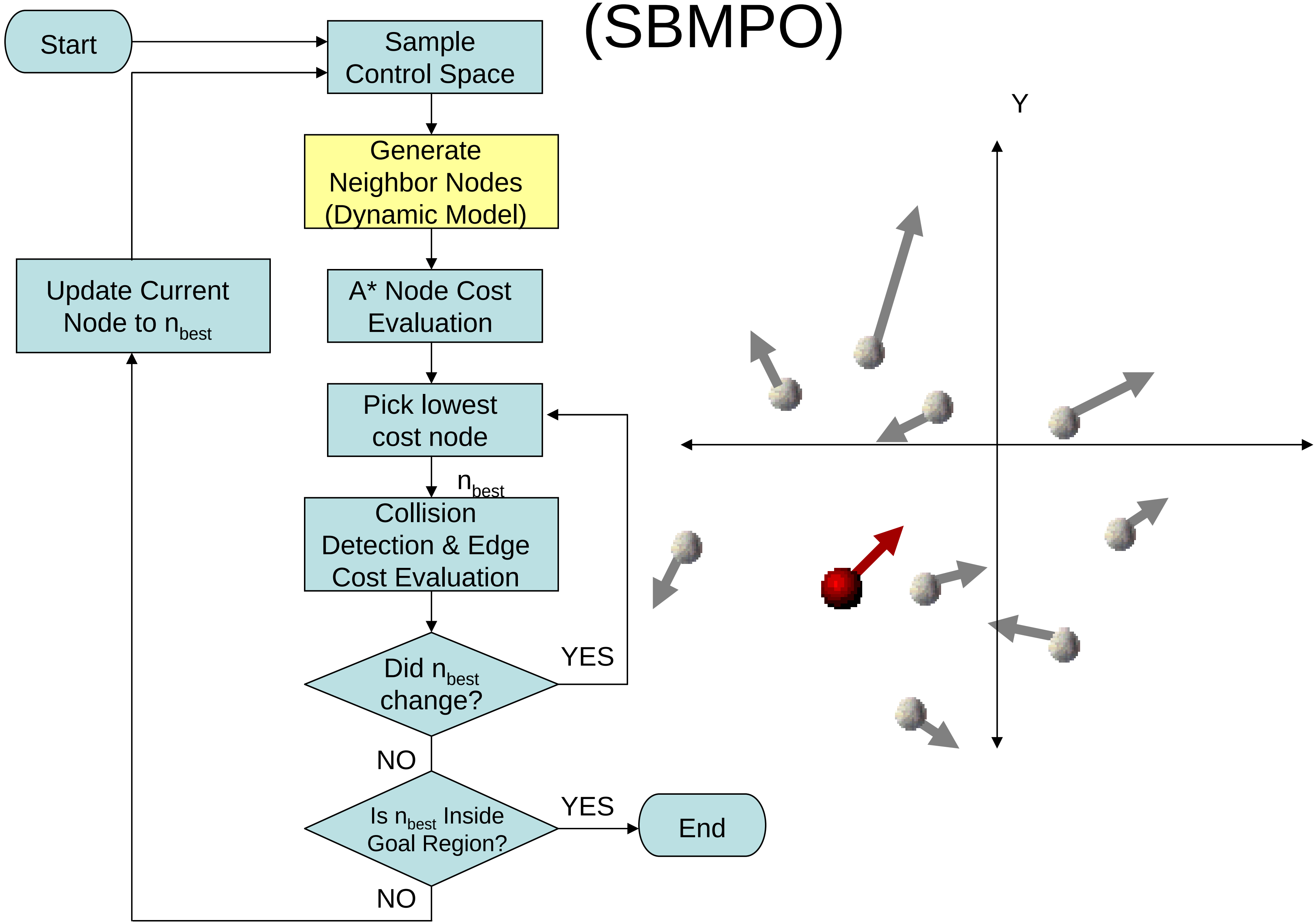

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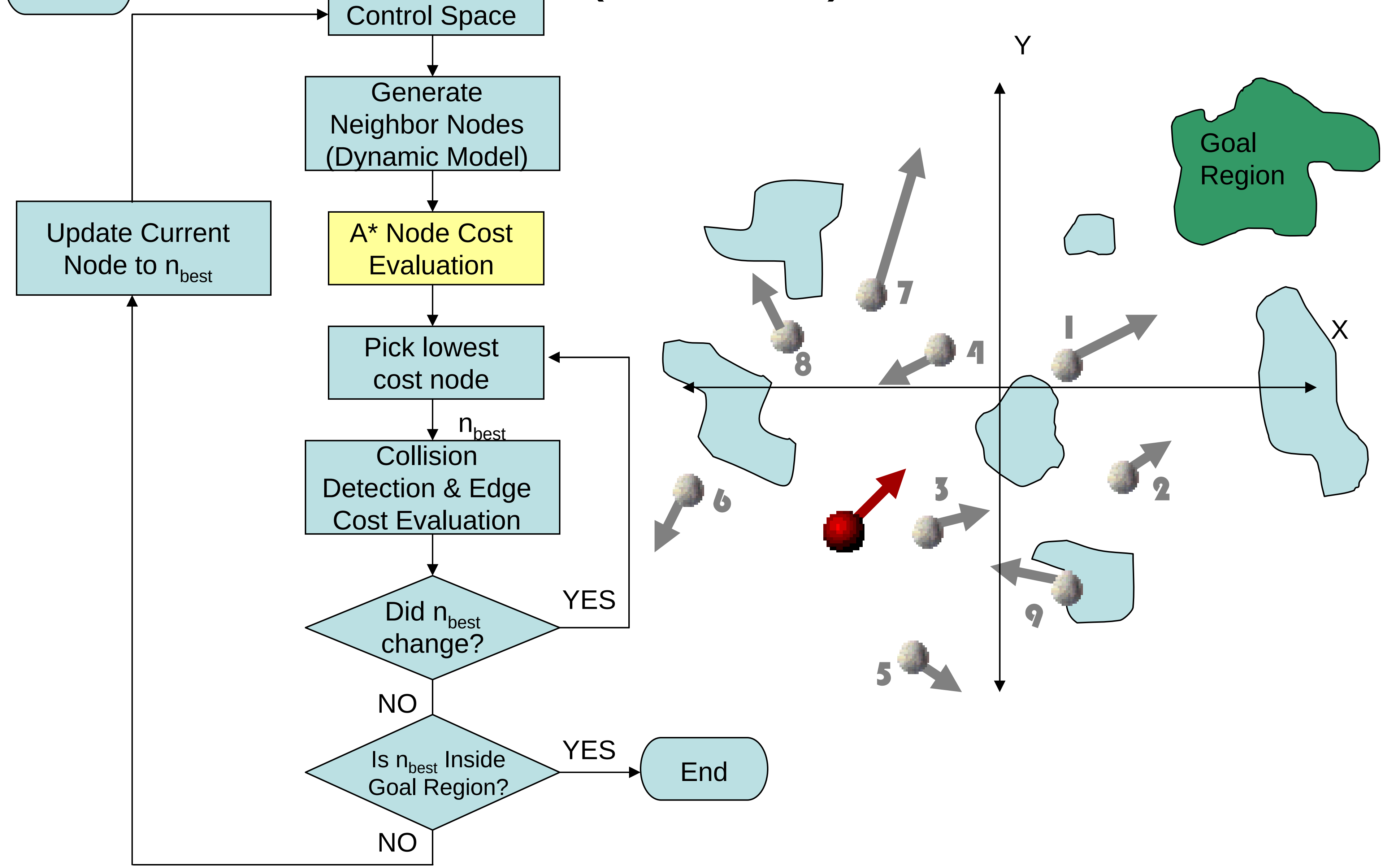

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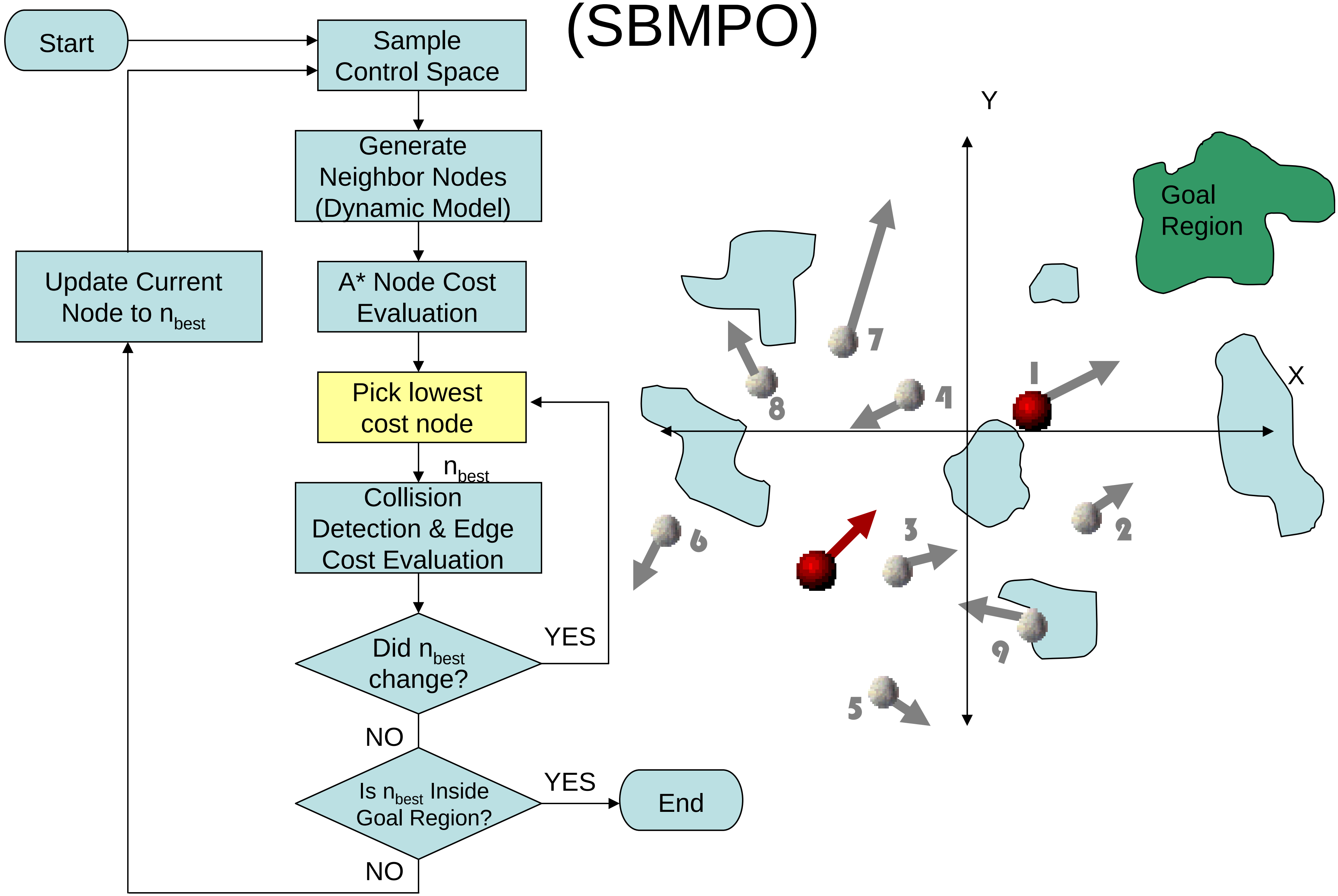

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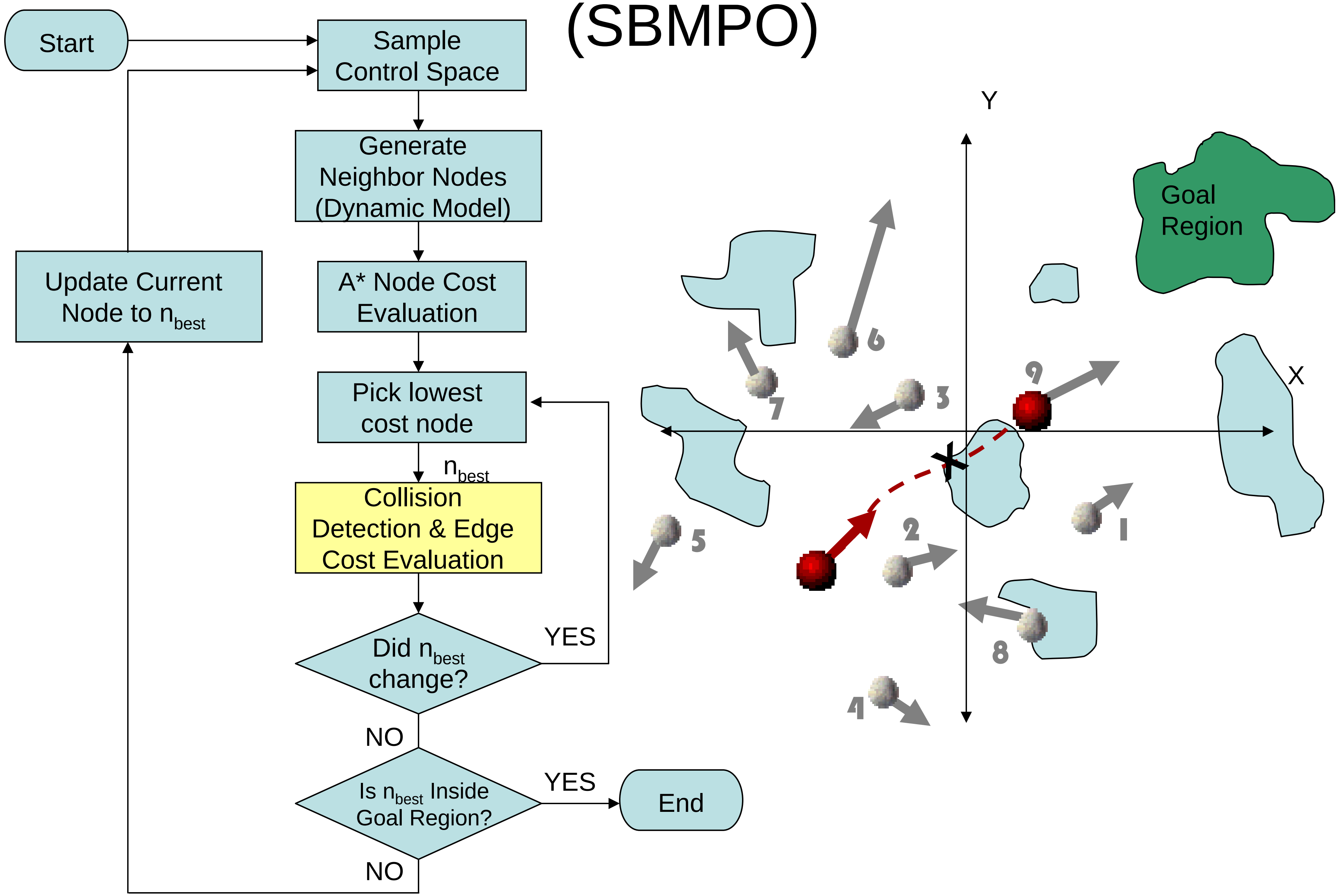

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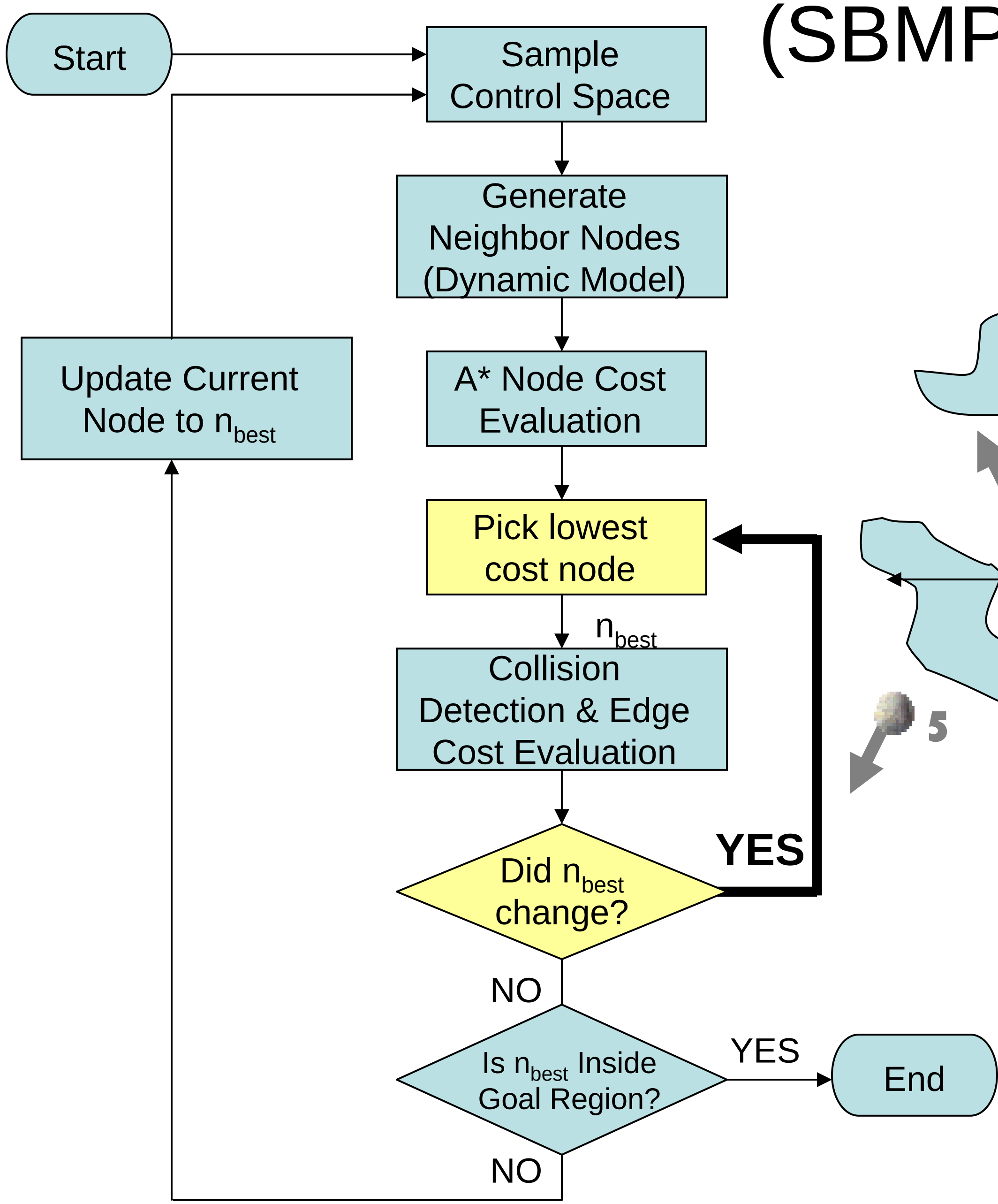

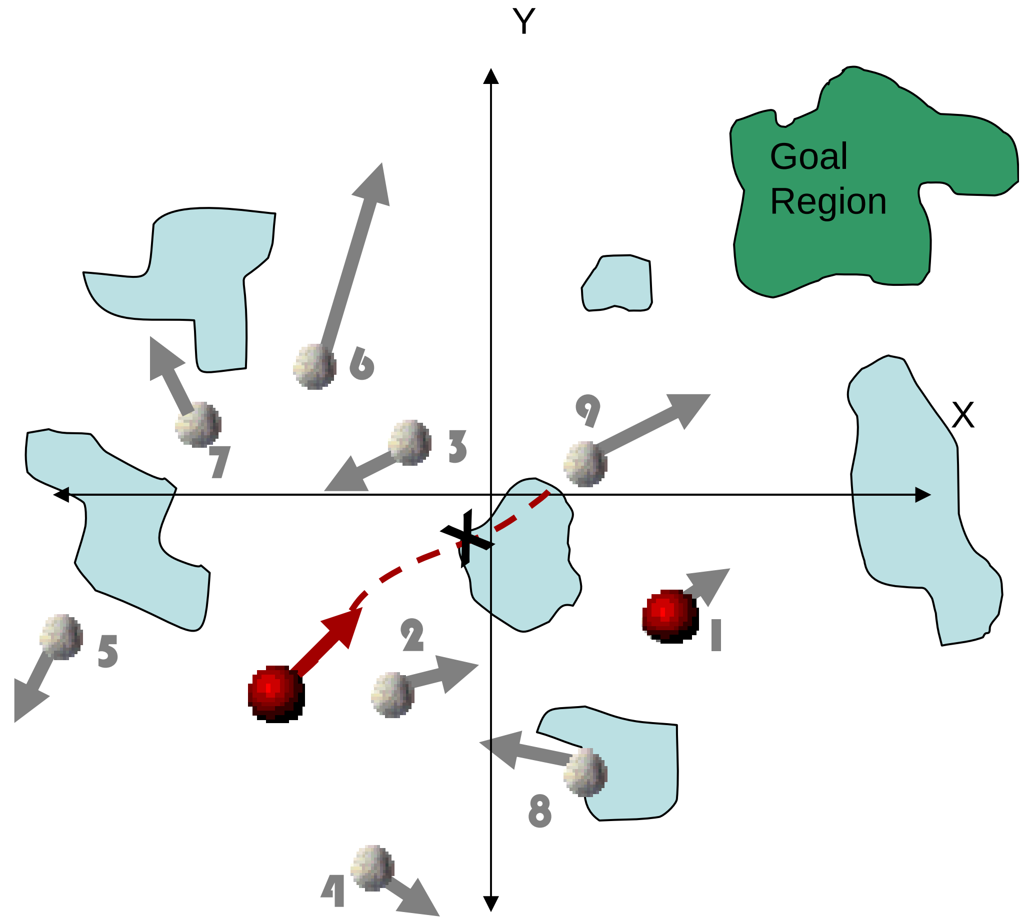

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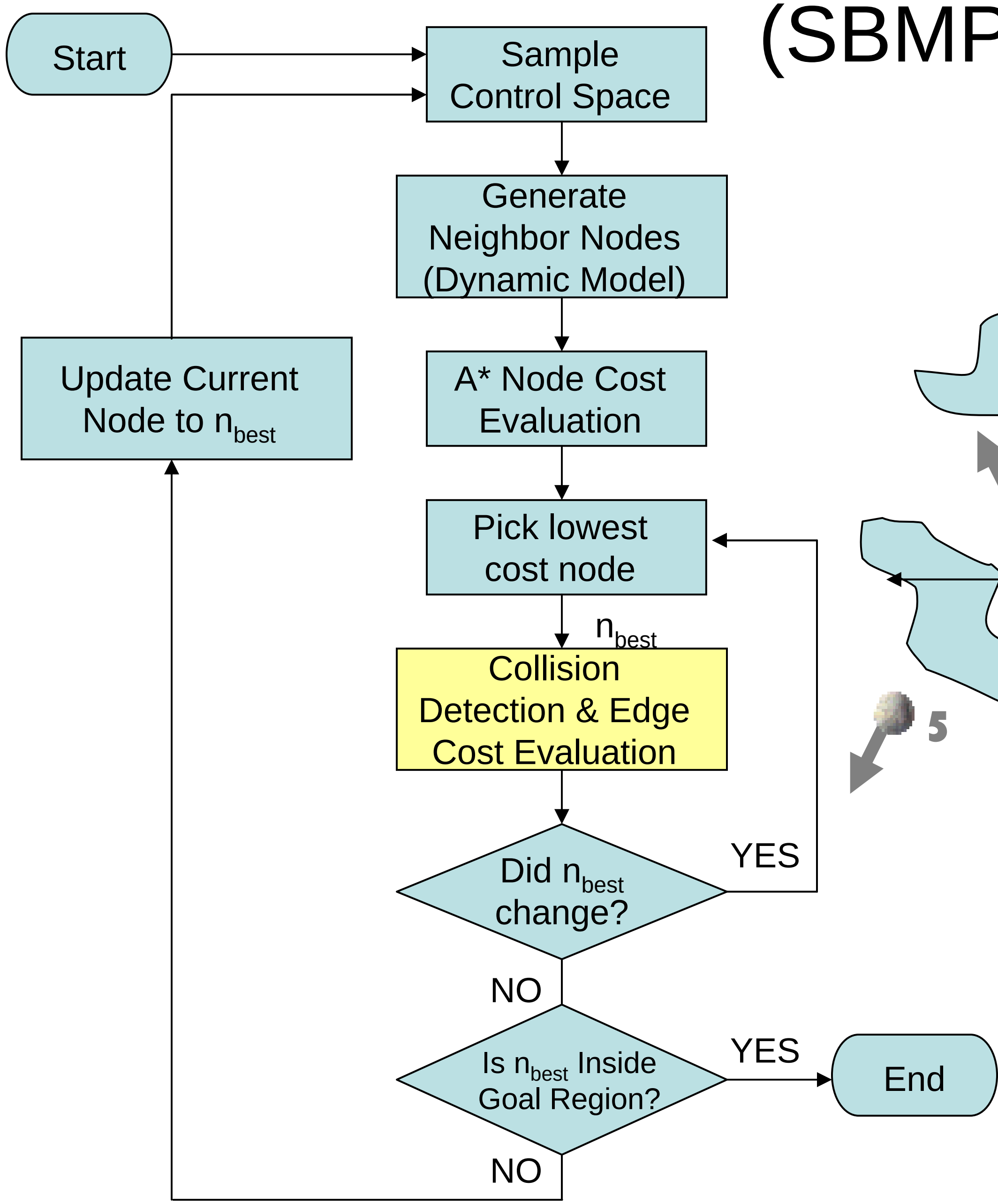

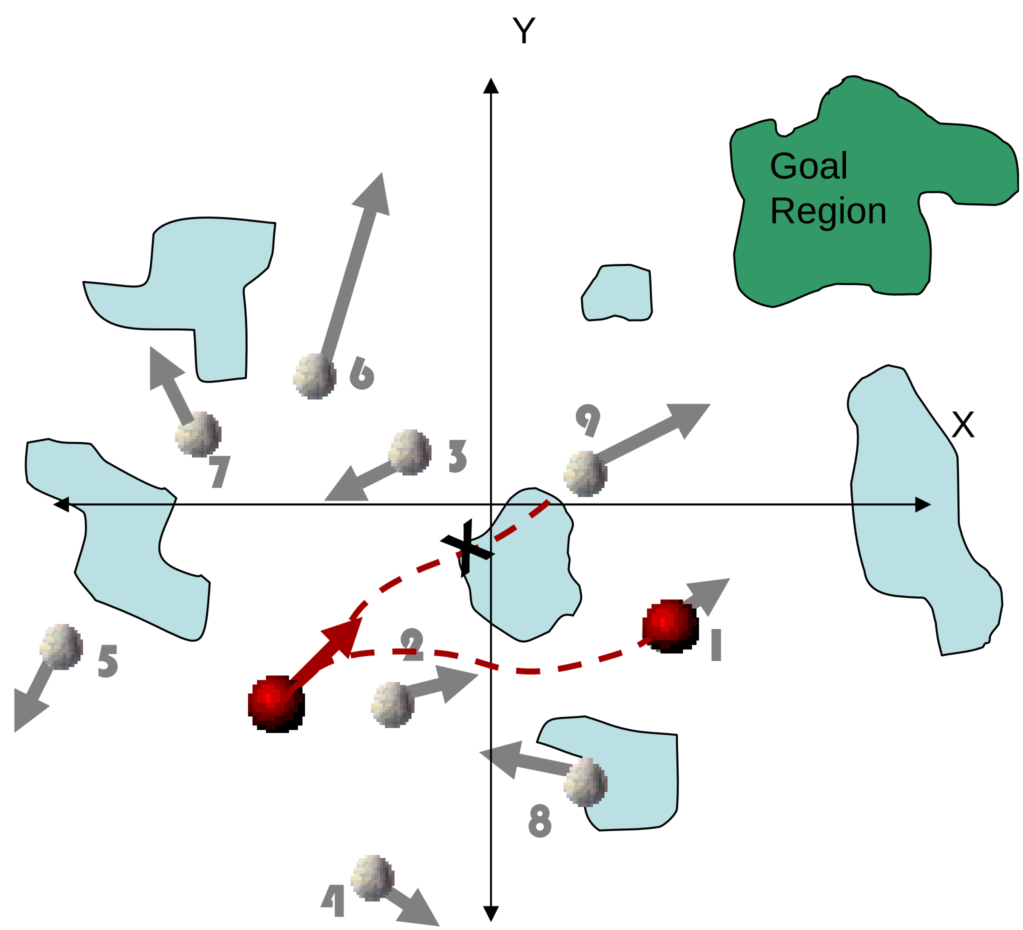

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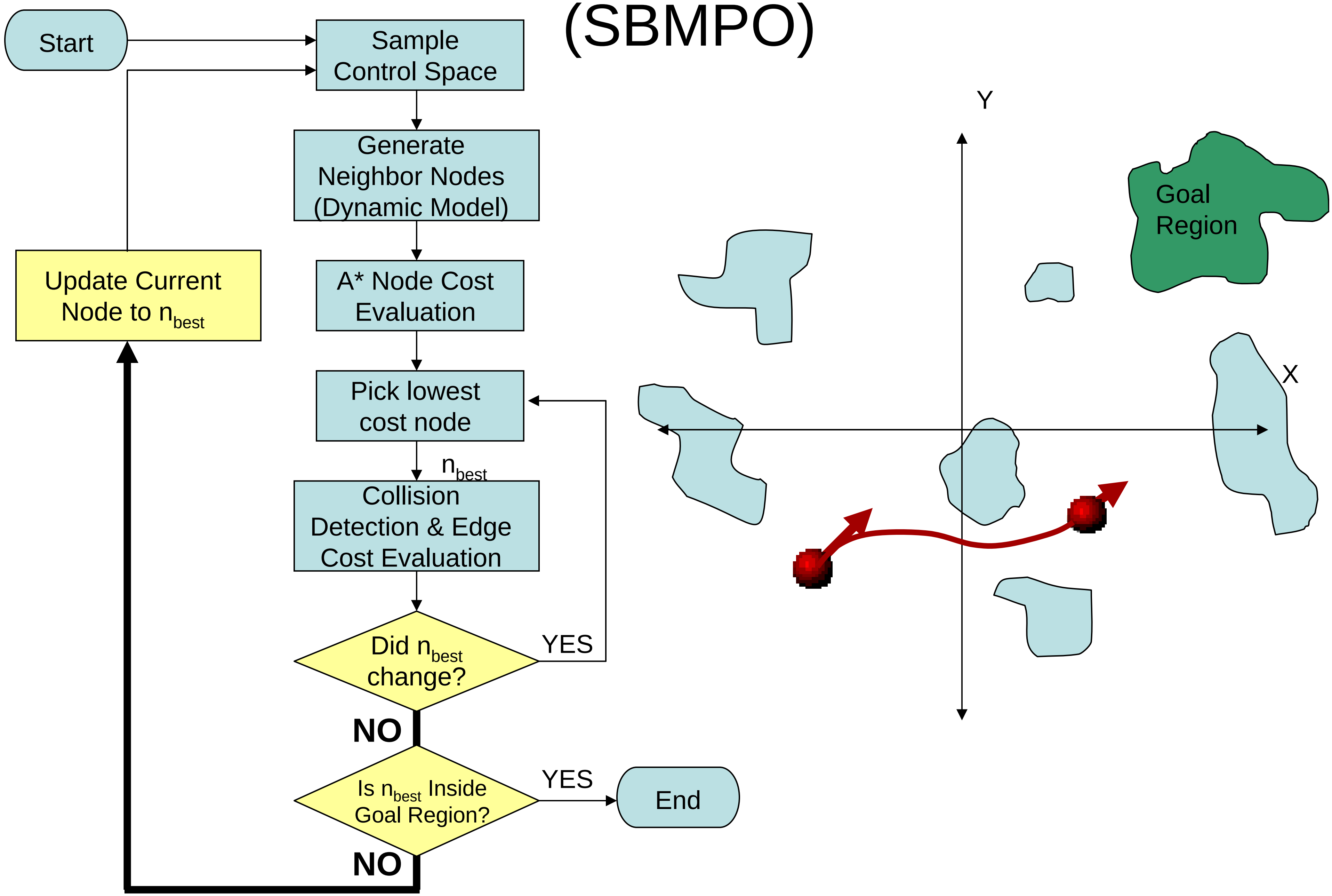

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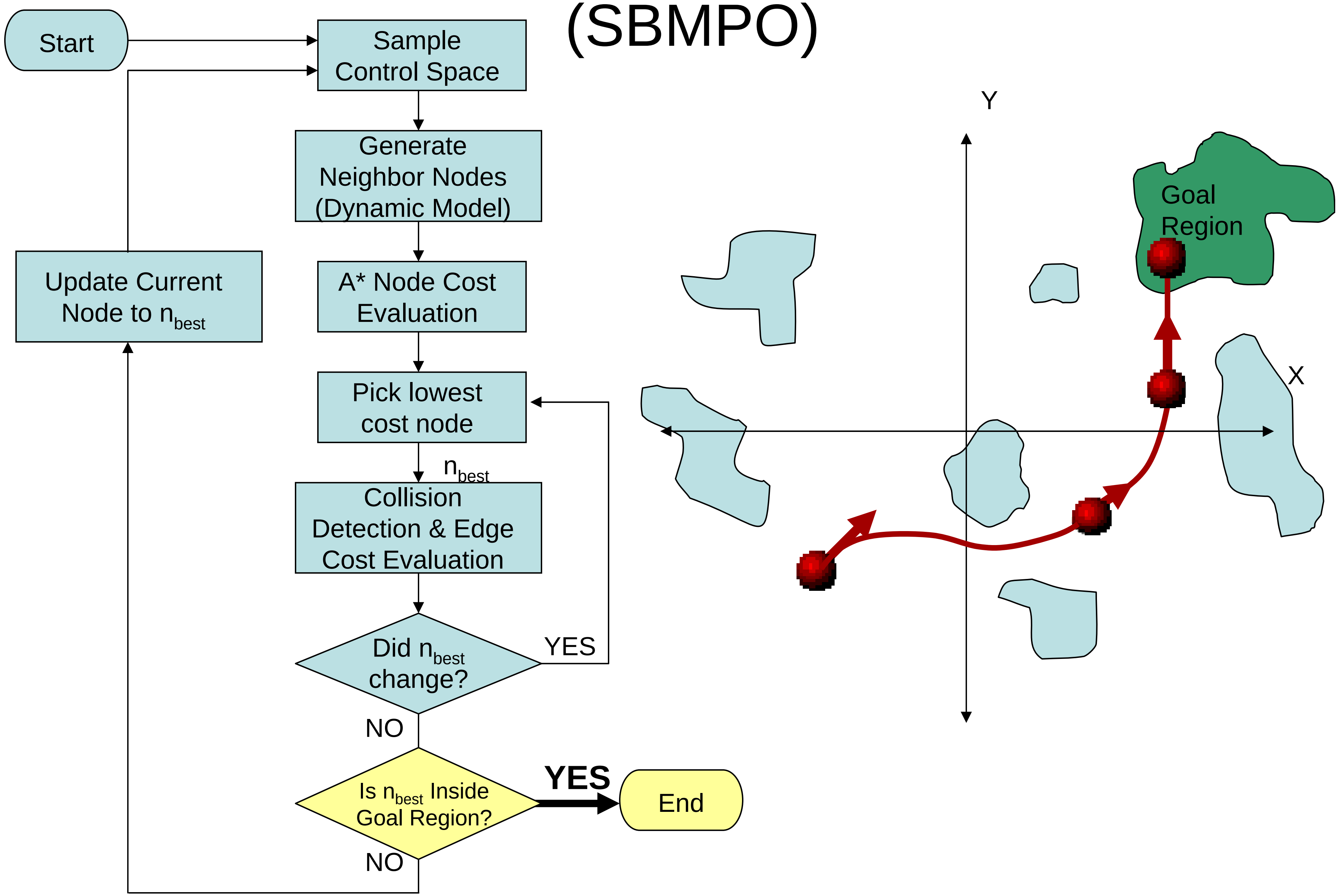
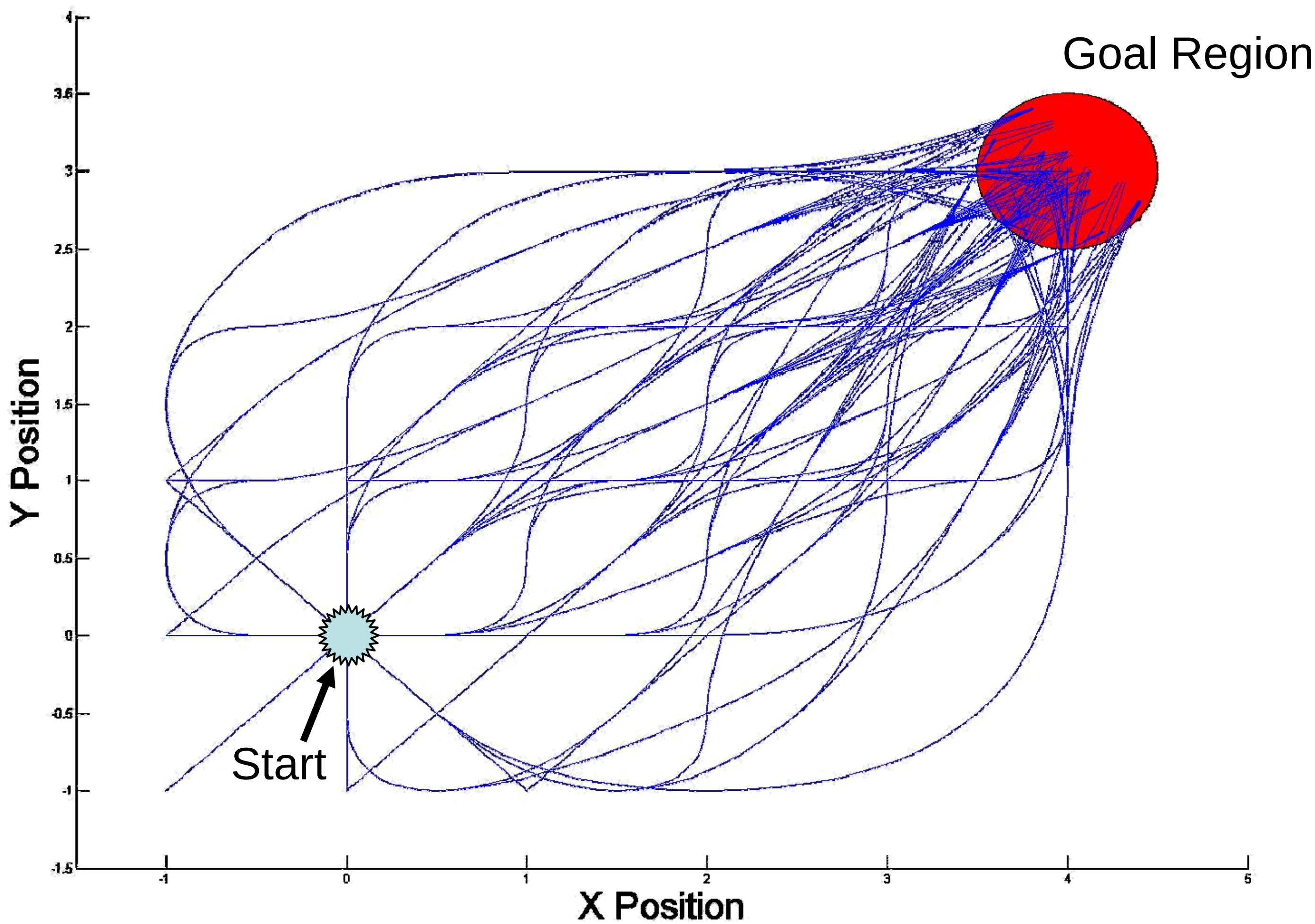
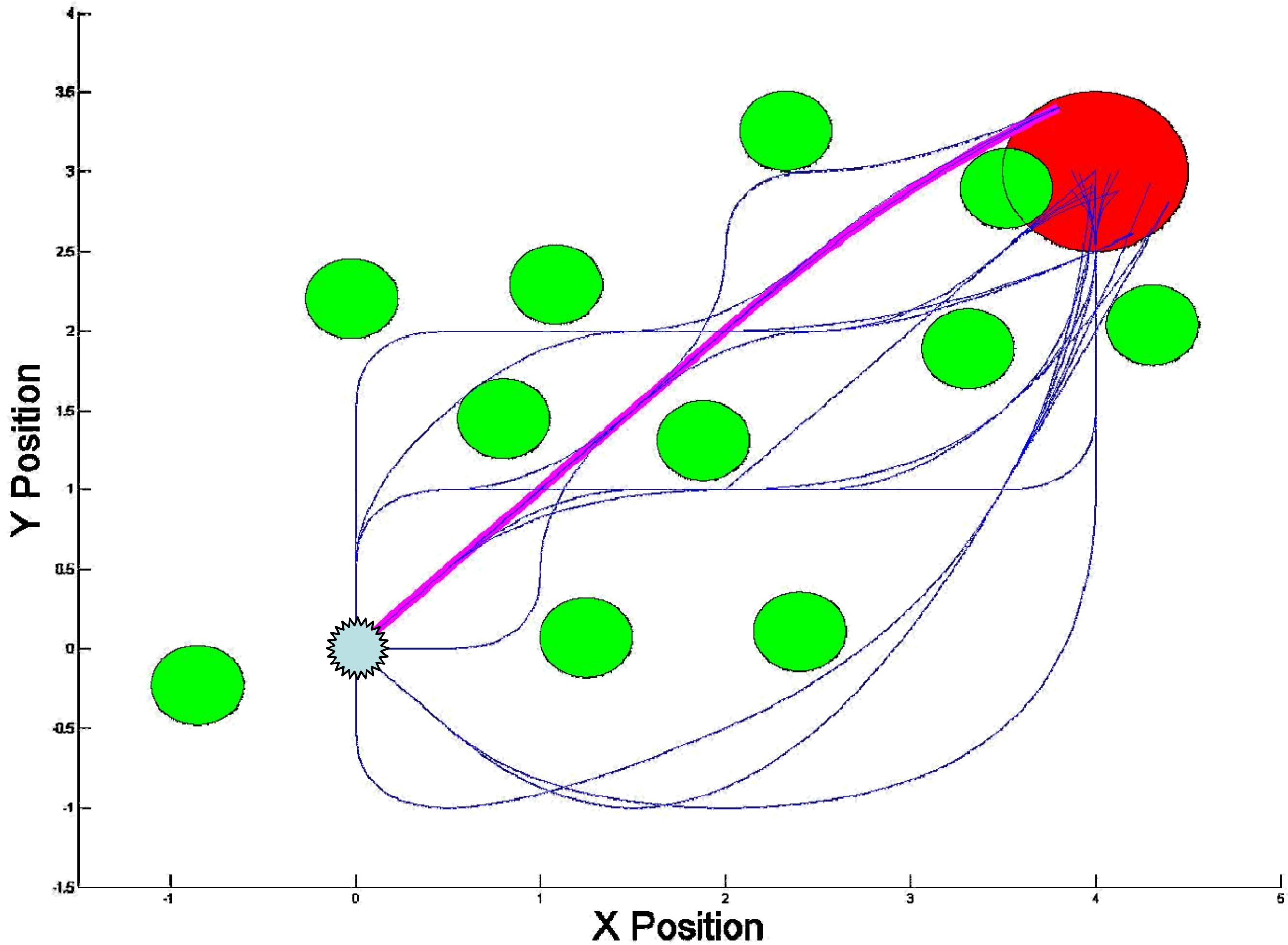


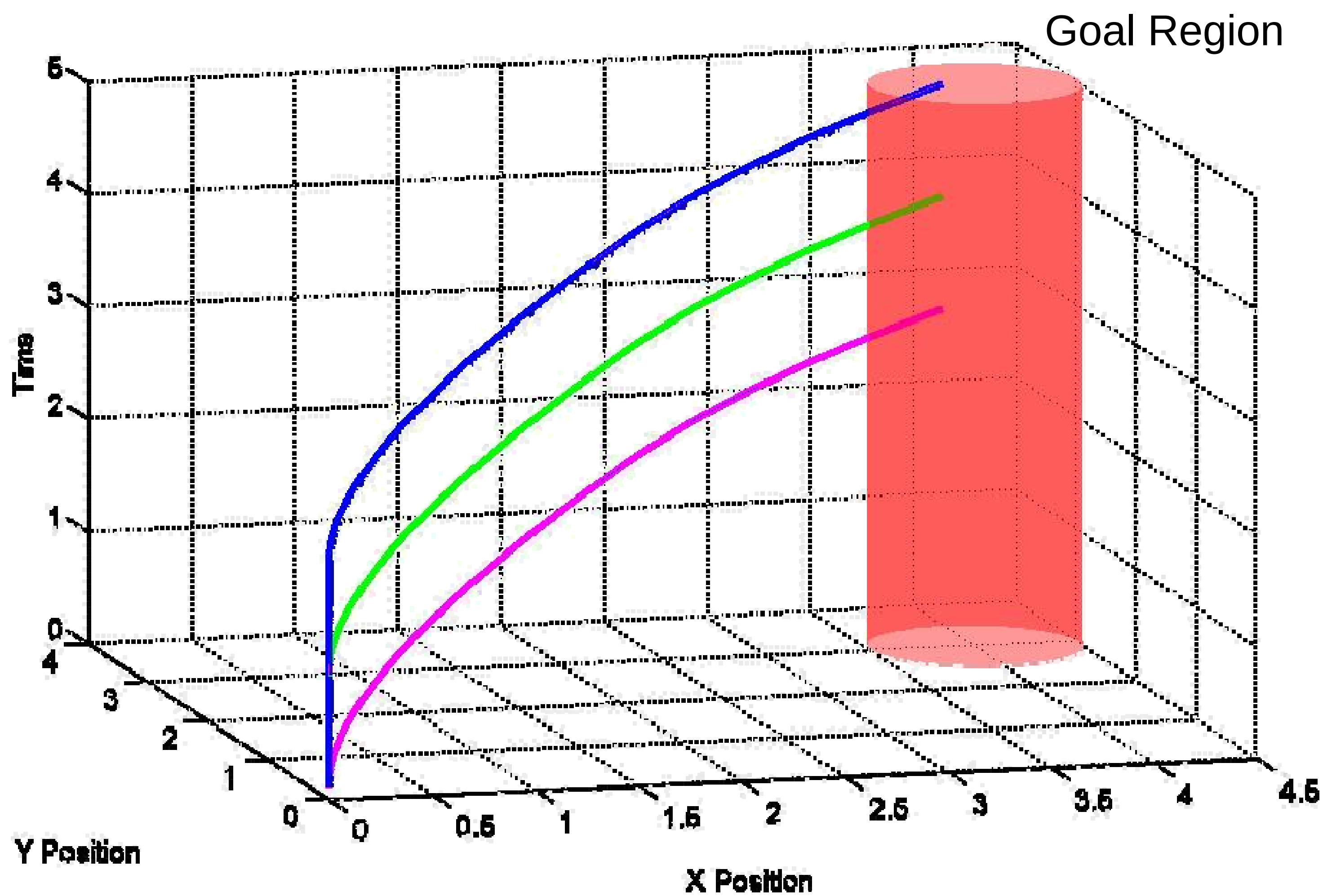
Preliminary Simulation Results:
Paths to Goal



Preliminary Simulation Results:
Obstacle Free and Time Optimal Paths



Preliminary Simulation Results:
Distance Optimal Paths



Problems to Be Solved Using Dynamic Models

- Path planning for climbing steep hills.
  - Need to plan velocity needed to reach the top.
  - A similar problem is rocking a vehicle out of a ditch.

Problems to Be Solved Using Dynamic Models

- Path planning for climbing steep hills.
  - Need to plan velocity needed to reach the top.
  - A similar problem is rocking a vehicle out of a ditch.

- Path planning for high speeds.
  - Important when travelling at high speeds around obstacles. (Slip needs to be taken into account.)
  - May allow a vehicle to emulate the efficient curve traversal of race car drivers.

Problems to Be Solved Using Dynamic Models (Cont'd)

At Grand Challenge

- Planning for Stability
  - Stability at high speeds and for small turn radii is essential for vehicle safety.

- Energy Efficient Path Planning
  - This research will involve the use of dynamic models to develop more accurate measures of the energy used to navigate a given path.
  - This is especially important in undulating environments with different terrain types.

Problems to Be Solved Using Dynamic Models (Cont'd)

- Obstacle Traversal
  - -This research will feed directly into our research on Control on Difficult Terrains.
- Path Planning in the Presence of Mechanical Failure
  - -An example of this is a flat tire.
  - -In this case the model changes and so may the most efficient paths.
- Path Planning in the Presence of Dynamic Obstacles

QUESTIONS?

USC Robotics Research Lab

Part I:
Constrained Trajectory Planning on Outdoor Terrain

Part II:
Optimal Motion Control of Nonholonomic Systems

Marin Kobilarov, Gaurav Sukhatme

Robotic Embedded Systems Laboratory
University of Southern California, Los Angeles, USA

Workshop on Mobility and Control in Challenging Environments
Olin College, Needham, MA
October 5 & 6, 2006

Part I:

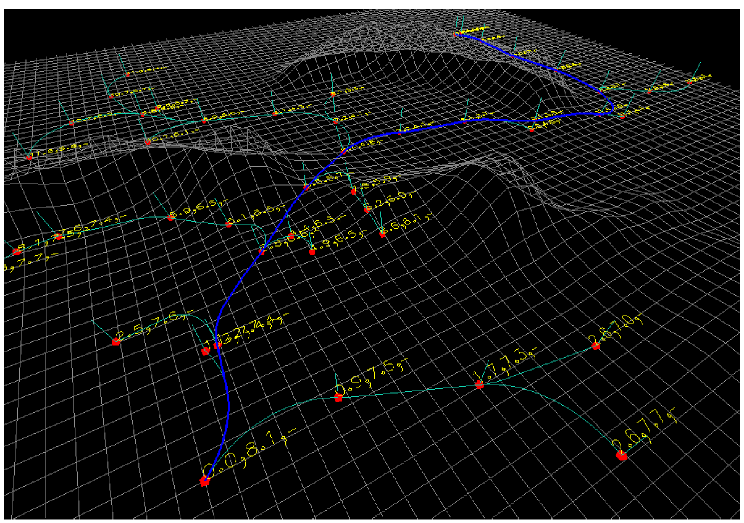
Constrained Trajectory Planning on Outdoor Terrain

Motion Planning Problem

- Given:
  - wheeled robot
  - coarse uneven terrain map
  - dynamic constraints

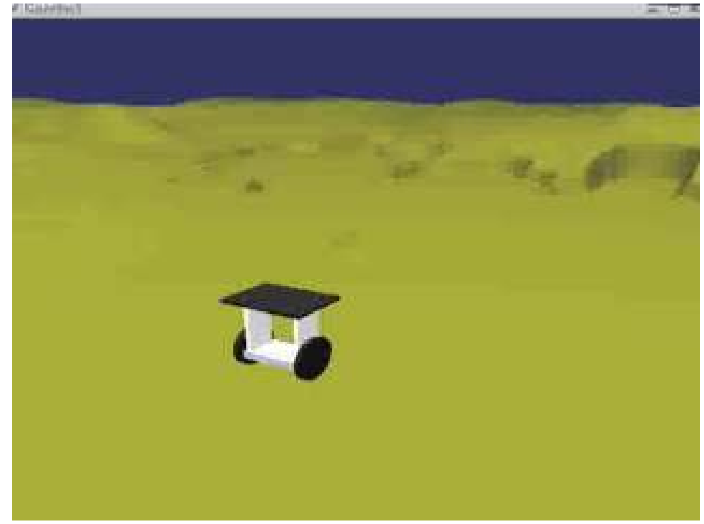
Segway RMP

- Compute:
  - shortest time feasible trajectory to a goal configuration



Assumptions

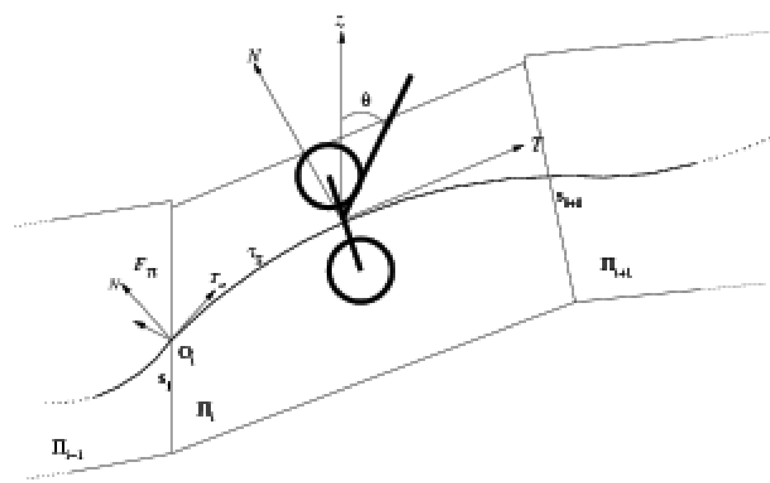
- Dynamics
  - – detailed physics-based simulation too costly
  - – empirically determine safe bounds
  - – assume robot wheels do not slip or slide
  - – assume the existence of a controller that can achieve controls in the vehicle envelope
  - – Example: Segway RMP
    - PID for velocity control,LQR for balancing



Dynamics simulator

- Planar Discretization

  Over a short path segment δ_g on terrain surface $\mathbf{G} \subset \mathrm{R}^3$ define:
  - – flat patch $\Pi \approx \{\mathbf{p}^i \mid \mathbf{p}^i \in \mathbf{G}, i = 1,\ldots,k\}$
  - – local ref. frame $\mathcal{F}_\Pi \in (\mathbf{G} \times \mathbf{SO}(3))$
  - – the robot transitions between patches after traveling distance of length δ_g



Discretized path

Robot Model and Constraints

- Simple differential drive model

$$\begin{pmatrix} \dot{x} \\ \dot{y} \\ \dot{\psi} \\ \dot{v} \\ \dot{\omega} \end{pmatrix} = \begin{pmatrix} v\cos\psi \\ v\sin\psi \\ \omega \\ 0 \\ 0 \end{pmatrix} + \begin{pmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{pmatrix} \mathbf{u}$$

  - x, y, ψ are position and orientation with respect to frame $\mathcal{F}_{\Pi}$
  - v, ω are forward and angular velocities
  - in addition we keep track of pitch θ and roll ϕ computed from the planar patch incline

- Bounds:
  - curvature: $|\kappa| < \kappa_{max},\ \hat{\kappa}_{max}(v) = 1/\hat{R}_{min}(v)$

    $\omega < v\kappa_{max}(v)$

  - dynamic: $\text{Velocity:} v < v_{max}$ stability: $\text{Pitch:} |\theta| < \theta_{max}$

    $\text{Acceleration:} |\dot{v}| < a_{max}$ $\text{Roll:} |\phi| < \phi_{max}$

Sampling Approach

- Control-system based Probabilistic RoadMaps *(Hsu et. al.)*
  - near optimal solution
  - near real-time performance

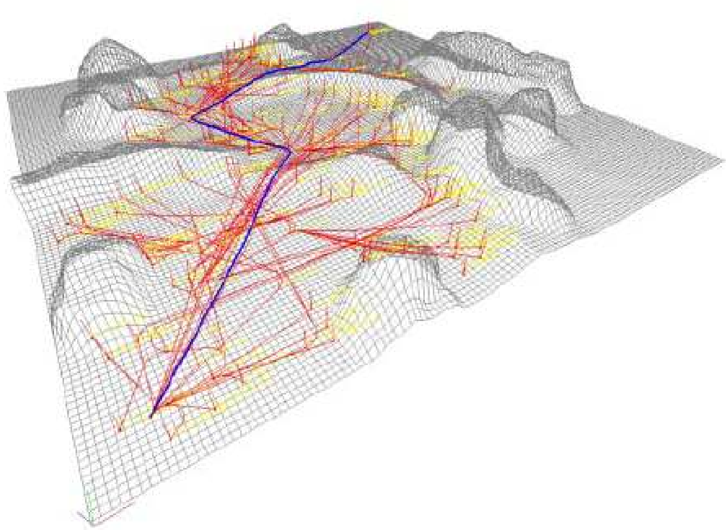
- Handle the dimensionality (NP-hard)

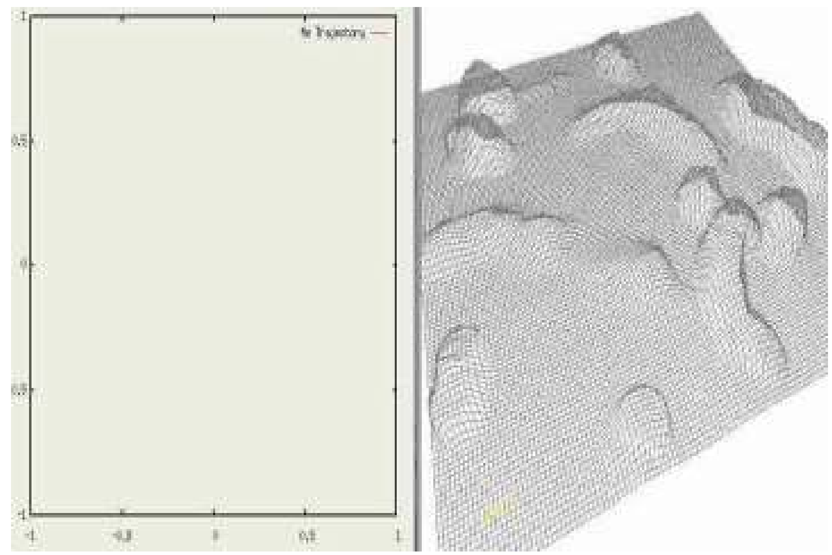
- Efficiently explore the state space by building a tree of nodes (connected with feasible trajectories) until the goal is reached

- Nonholonomic constraints automatically satisfied by the forward model

Randomized Kinodynamic Solution

- Control-system based Probabilistic RoadMap
  - sampling in position space
  - probabilistic and resolution complete
- Implementation: based on *Frazzoli, Dahleh, Feron, 2000*
  - expansion heuristics (A*-like)
  - pruning techniques





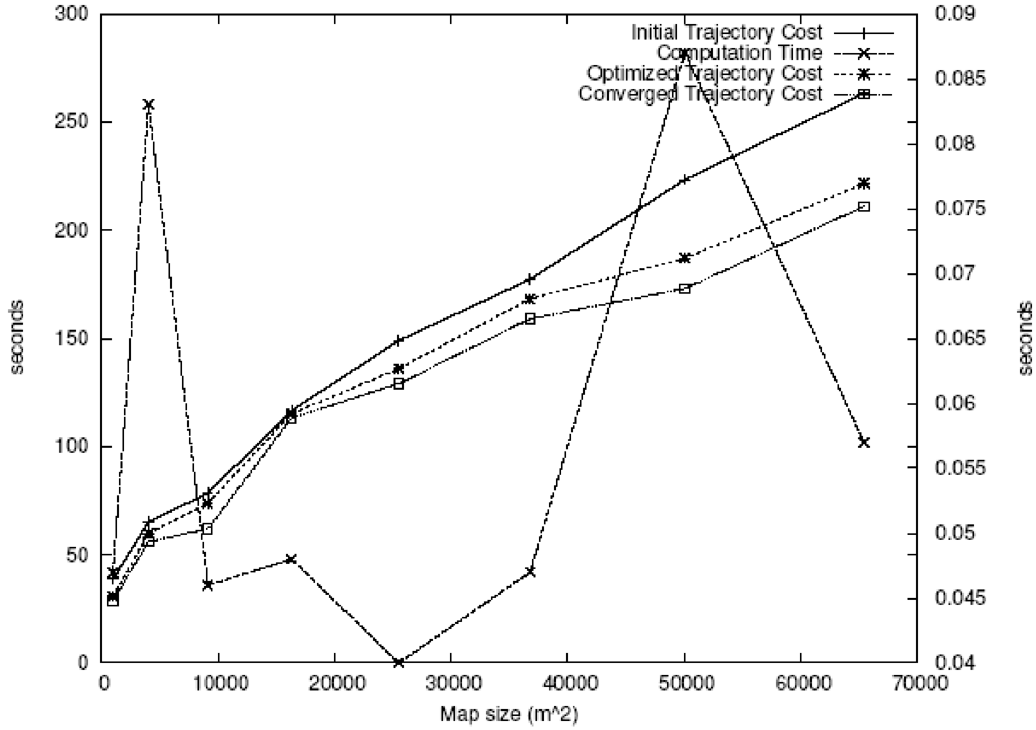
PRM on artificial terrain

Local Steering Method

- How is the system steered towards new milestones?
  - terrain induces a velocity and acceleration limits
  - curvature constraints further limit the control choice
  - Choose bang-bang controls within the dynamic bounds that satisfy the curvature constraints
  - Hard to determine time-optimal switching times
- Decoupled approach:
  - find the shortest path that satisfies the curvature constraint: *clothoid with trapezoidal curvature profile*
  - bang-bang angular acceleration control along curved path segment
  - bang-bang linear acceleration control along straight path segment
  - not guaranteed to be optimal but a good choice locally
- A more optimal solution can be found numerically *(see second part of the talk)*

Simulations

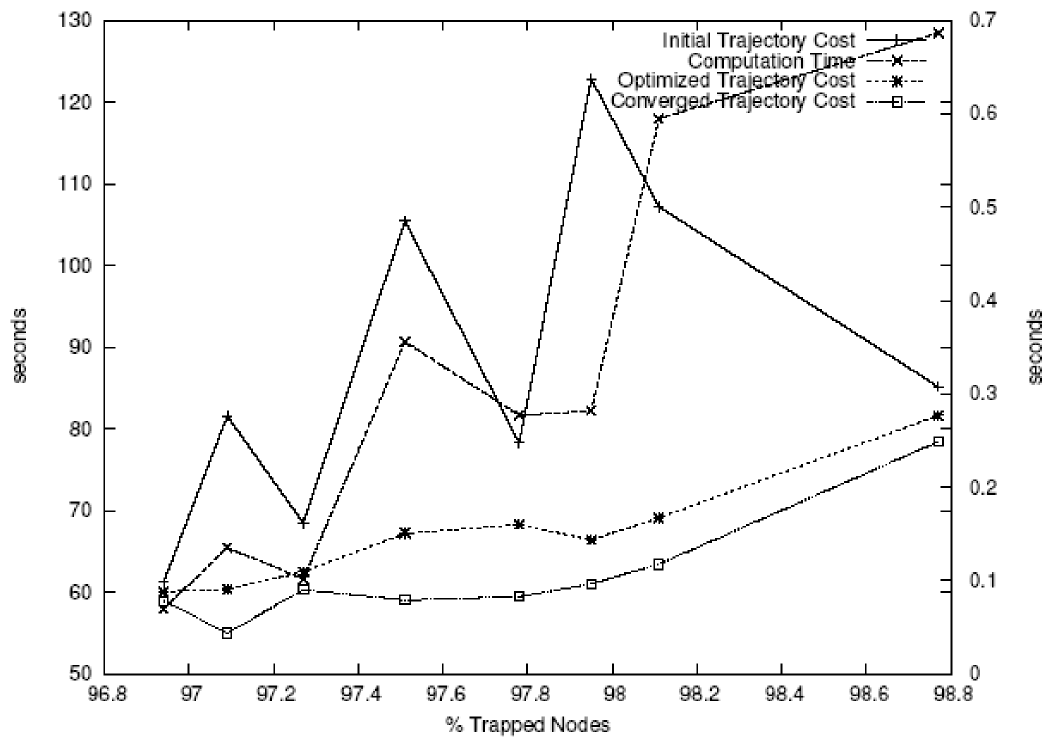
- Trajectory Cost (left y-axis) vs. Map Size
- Computation Time (right y-axis) vs. Map Size



- Good convergence and runtime in large maps

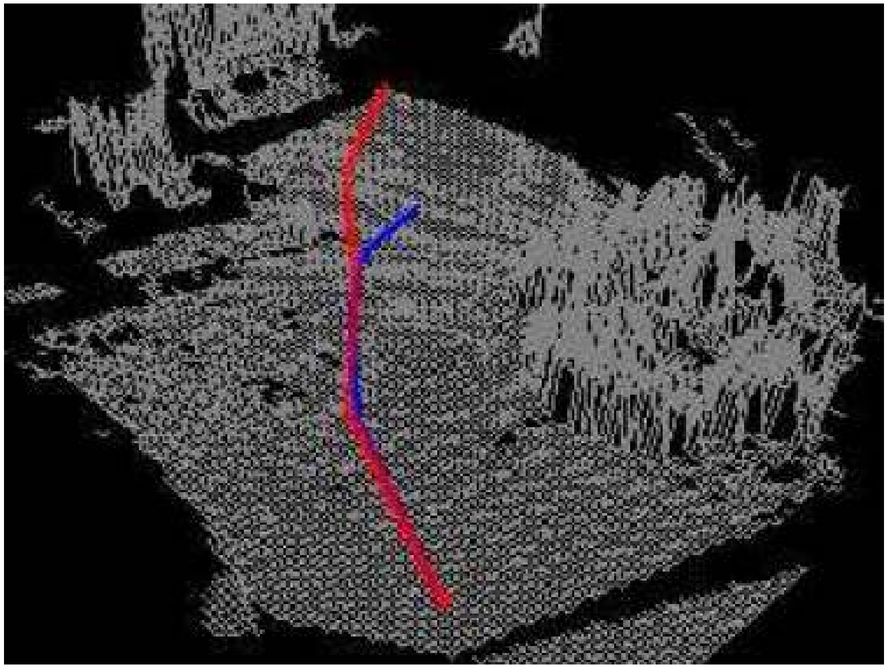
Simulations

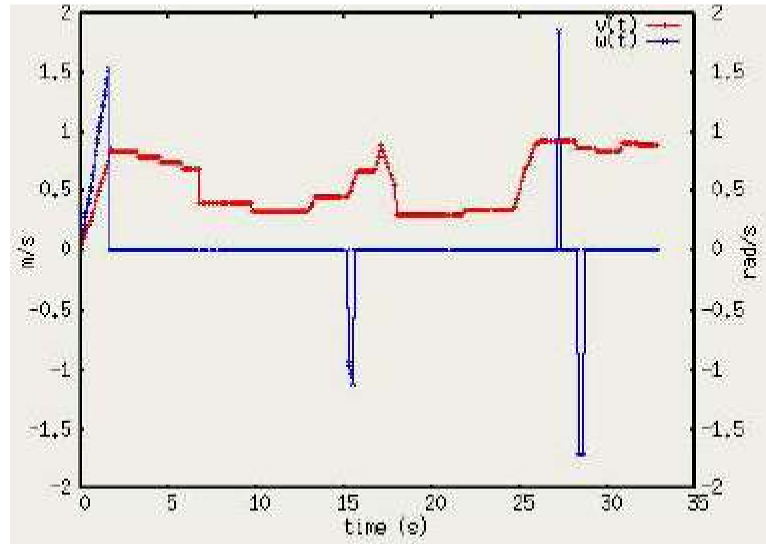
- Trajectory Cost (left y-axis) vs. % trapped nodes
- Computation Time (right y-axis) vs. % trapped nodes



- Efficiently finds near-optimal trajectory in terrains of different expansiveness

Robot Experiments





- Blue – computed path
- Red - executed

- Blue – angular velocity profile
- Red – linear velocity profile

Conclusions

- Relaxing some of the requirements for terrain modeling allows for efficient kinodynamic planning
- The solutions are not necessarily feasible but are practical when precise terrain maps are unavailable
- More accurate models are required to produce fully executable paths
- In the future, we will focus on employing better models without losing near real-time performance

Part II:

Optimal Motion Control of Nonholonomic Systems

Motion Planning and Constrained Optimization

- Consider systems with drift and nonintegrable velocity constraints, e.g. a car-like robot moving at high speed
- One way to compute locally optimal motions is to solve a nonlinear constrained optimization problem
- *Discretize the equations of motion* and use them as constraints in an optimization of a given cost functional
- Any additional constraints are expressed as (in)equality constraints on the configurations and velocities
- The solution is a *discrete trajectory* and a discrete control curve (or a finite set of control parameters)

USC Robotics Research Lab

Motion Planning and Constrained Optimization

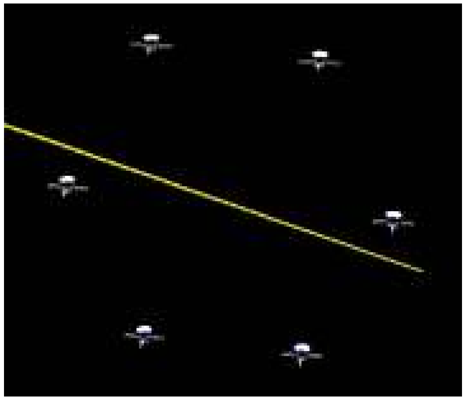
- Some recent *examples in robotics*:
  - *Milam, Mushambi, Murray* – constrained trajectory generation, differential flatness
  - *Kelly, Nagy, Howard* – parametric optimal control, rough terrain
  - *Cheng, Frazzoli, LaValle* – improving precision, closing gaps, exploiting symmetries
  - *Dever, Mettler, Feron, Popovic* – trajectory generation, parameterized maneuver classes
  - *Lamiraux, Bonnafous, Lefebvre* – path deformation
- All optimization approaches have one *common aspect*: there is some form of discretization of the dynamics (e.g. when integrating the equations of motion or when enforcing the constraints)

Discrete Mechanics

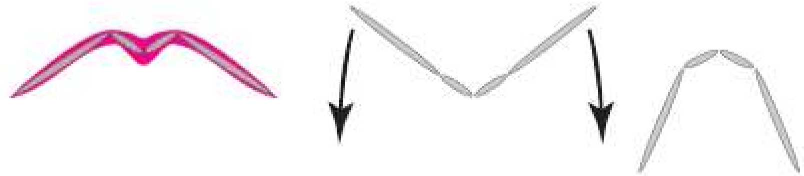
- A recently developed theory for discretizing the dynamics of physical systems
- Based on the discretization of variational principles[1] (roots in the discrete optimal control from the 1960's)
- Results in higher order integrators
- Preserves Structure: symplectic and momentum conservation (in the absence of forces), approximately respects the energy balance
- Discrete reduction analogs
- Performs well in both conservative and forced systems

[1] J. Marsden and M. West, "Discrete mechanics and variational integrators", *Acta Numerica*, 2001.

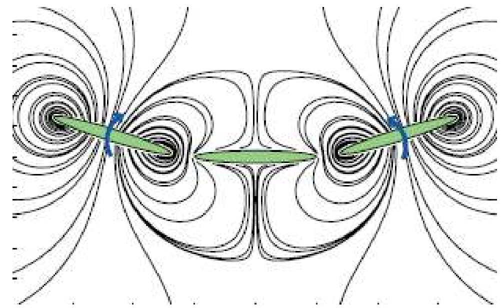
Discrete Mechanics



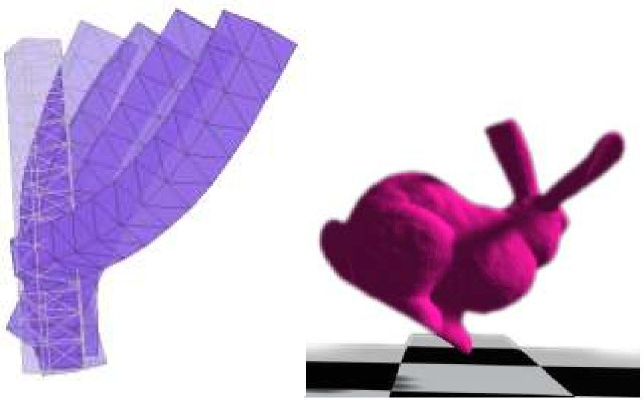
Space Mission Design (Junge et al, 2005)



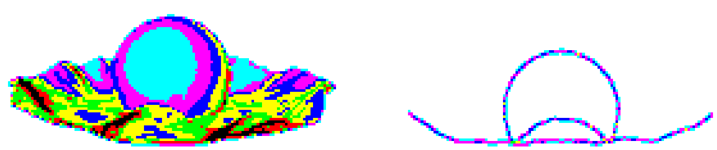
Optimal flapping strokes (Ross, 2005)



Optimal motions in fluid (Kanso et al, 2005)

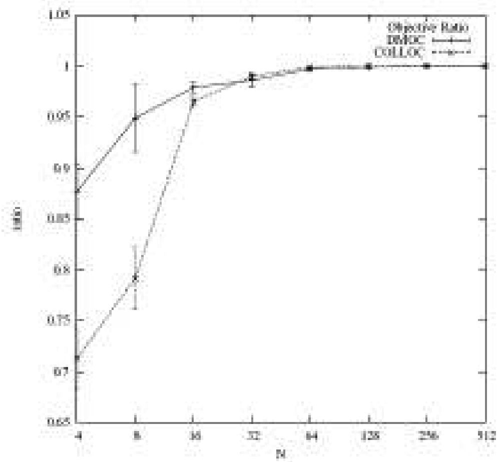


Elasticity Simulation (Kharevych et al, 2006)

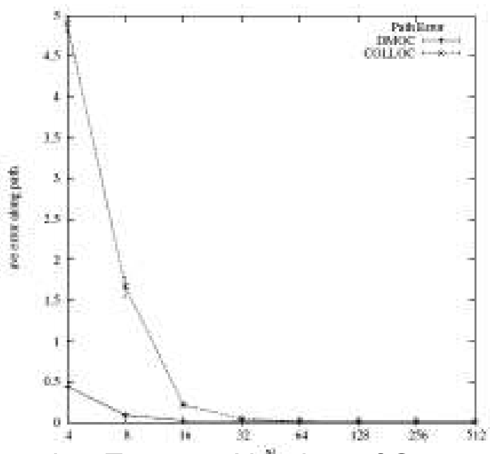


Nonsmooth finite element contacts
(Cirak, West, 2005)

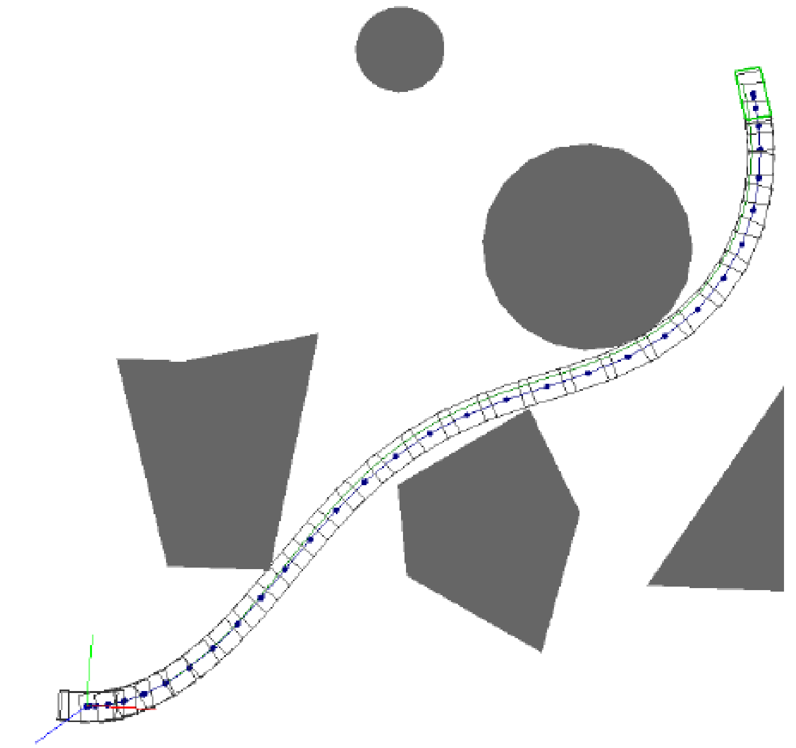
Motion planning with Nonholonomic Discrete Mechanics



Convergence vs. Number of Segments (N)



Execution Error vs. Number of Segments (N)

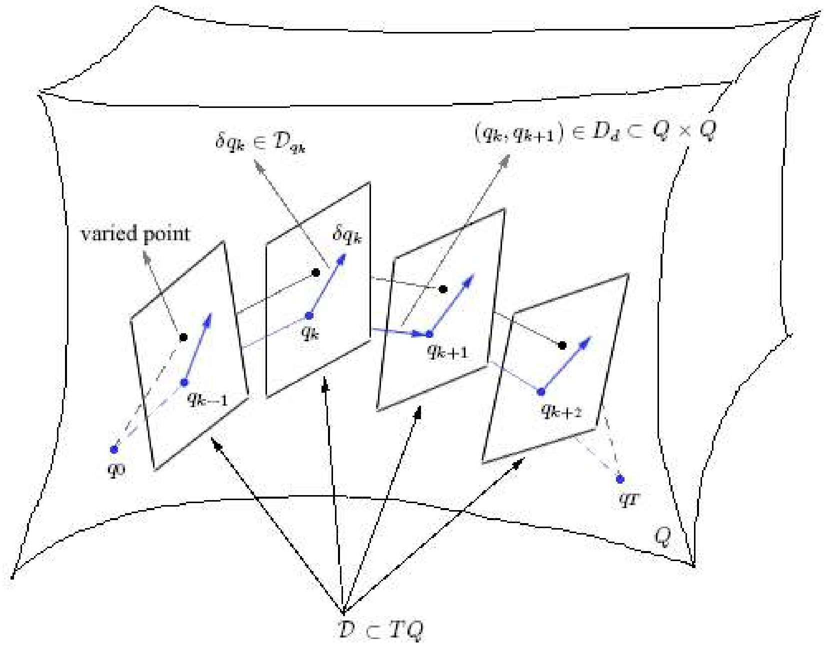


- Example: *car-like robot* among obstacles[4]
- Improved efficiency and convergence over standard collocation method (graphs)
- Allows coarser discretization (larger time steps)

[4] Marin Kobilarov, Gaurav Sukhatme, "Optimal motion control of nonholonomic systems", 2006, preprint

Discrete Variational Principle

- A path in a configuration manifold Q is represented by a discrete sequence of points
- The tangent bundle TQ replaced by the product $Q \times Q$



- The nonholonomic distribution $\mathcal{D} \subset TQ$ replaced by a discrete analog $\mathcal{D}_d \subset Q \times Q$

Discrete Variational Principle

- Approximate the action integral between two consecutive points using discrete Lagrangian:

$$L_d(q_k, q_{k+1}) \approx \int_{kh}^{(k+1)h} L(q(t), \dot{q}(t))\mathrm{d}t$$

- The *virtual work* of control force $f : [0, T] \rightarrow T^*Q$ is approximated on each segment by:

$$f_k^- \cdot \delta q_k + f_k^+ \cdot \delta q_{k+1} \approx \int_{kh}^{(k+1)h} f(t) \cdot \delta q(t)\mathrm{d}t$$

where $f_k^-, f_k^+ \in T^*Q$ are called *left* and *right* discrete control forces

Discrete Lagrange-D'Alembert Principle

- The discrete nonholonomic Lagrange-D'Alembert principle[2] can be derived as:

$$\delta \sum_{k=0}^{N-1} L_d(q_k, q_{k+1}) + \sum_{k=0}^{N-1} f_k^- \cdot \delta q_k + f_k^+ \cdot \delta q_{k+1} = 0$$

$$\delta q_0 = \delta q_N = 0 \qquad \delta q_k \in \mathcal{D}_{q_k}, (q_k, q_{k+1}) \in \mathcal{D}_d \text{ for all } k = 0, ..., N-1$$

- Expressing the constraints as $\delta s^a + A^a_\alpha \delta r^\alpha = 0$, $q = (r, s)$ the discrete nonholonomic Euler-Lagrange equations read:

$$\frac{\partial L_k}{\partial r_k^\alpha} + \frac{\partial L_{k-1}}{\partial r_k^\alpha} + (f_k^{R-})_\alpha + (f_{k-1}^{R+})_\alpha = A^a_\alpha(r_k, s_k)\left(\frac{\partial L_k}{\partial s_k^a} + \frac{\partial L_{k-1}}{\partial s_k^a} + (f_k^{S-})_a + (f_{k-1}^{S+})_a\right)$$

$\omega_d^a(r_k, s_k, r_{k+1}, s_{k+1}) = 0$, where $\omega_d^a : Q \times Q \to \mathbb{R}$ define $\mathcal{D}_d$

[2] J. C. Monforte, *Geometric, Control and Numerical Aspects of Nonholonomic Systems*. Springer, 2002.

Discrete Nonholonomic Optimal Control

- For optimal control we discretize the cost functional[3]:

$$J(q,\dot{q},f) = \int_0^T C(q(t),\dot{q}(t),f(t))\mathrm{d}t$$

using a quadrature approximation on each segment

$$C_d(q_k,q_{k+1},f_k,f_{k+1}) \approx \int_{kh}^{(k+1)h} C(q,\dot{q},f)dt$$

to derive the total cost

$$J_d(q_d,f_d) = \sum_{k=0}^{N-1} C_d(q_k,q_{k+1},f_k,f_{k+1})$$

[3] O. Junge, J. Marsden, S. Ober-Blöbaum, “Discrete Mechanics and Optimal Control”, IFAC, 2005

Discrete Nonholonomic Optimal Control

- An example discretization scheme: MIDPOINT RULE

$$\begin{aligned}
&C_d(q_k, q_{k+1}, f_k, f_{k+1}) \\
&\qquad = hC\left(\frac{q_k + q_{k+1}}{2}, \frac{q_{k+1} - q_k}{h}, \frac{f_k + f_{k+1}}{2}\right), \\
&L_d(q_k, q_{k+1}) = hL\left(\frac{q_k + q_{k+1}}{2}, \frac{q_{k+1} - q_k}{h}\right), \\
&\omega_d^a(q_k, q_{k+1}) = \omega^a\left(\frac{q_k + q_{k+1}}{2}, \frac{q_{k+1} - q_k}{h}\right), \\
&\int_{kh}^{(k+1)h} f(t) \cdot \delta q(t) \mathrm{d}t \approx h \frac{f_k + f_{k+1}}{2} \cdot \frac{\delta q_k + \delta q_{k+1}}{2} \\
&\qquad = \frac{h}{4}(f_k + f_{k+1}) \cdot \delta q_k + \frac{h}{4}(f_k + f_{k+1}) \cdot \delta q_{k+1}
\end{aligned}$$

- Other discretization schemes are possible leading to higher order integrators: i.e. symplectic-partitioned Runga-Kutta, Verlet, etc

Discrete Nonholonomic Optimal Control

- Optimization Algorithm Summary
  - Represent an initial trajectory by a *discrete path* of N segments
  - Form the *discrete cost functional*, *discrete lagrangian*, *discrete constraint distribution*, and *discrete analog of virtual work*
  - Express the discrete Euler-Lagrange equations as constraints
  - Add boundary conditions and any other constraints/bounds
  - Solve directly using Sequential Quadratic Programming

- Remarks
  - The equations of motion are replaced by their discrete variational counterpart
  - The algorithm uses only algebraic constraints (no derivatives)
  - Good performance even at coarse resolution (big time steps)
  - Potential advantages over standard “brute-force” discretization used in standard collocation, shooting, multiple shooting methods

Discrete Nonholonomic Optimal Control

- Summary
  - Optimal control method based on the *discretization of Lagrange-d'Alembert principle of virtual work*
  - Resulting *discrete variational equations* and *discrete nonholonomic constraints* of motion are used as algebraic constraints in a nonlinear program
  - We[4] are able to show improved efficiency over standard methods
  - Discrete Lagrangian reduction can also by applied to simplify the equations of motion (in the presence of symmetries) and further improve efficiency
- Many possible applications: e.g. complex environments, multiple vehicles, natural multi-resolution methods, global search ideas, etc…

[4] Marin Kobilarov, Gaurav Sukhatme, "Optimal motion control of nonholonomic systems", 2006, preprint

ARO Workshop on Mobility and Control in Challenging Environments

Olin College, Needham MA
October 5 & 6, 2006

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